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Mapping patterns of agricultural land-use intensity across Europe

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I am grateful to be born in a place and a time where one can decide to become what one wants to be or change one's life direction. I worked for a long time as a carpenter before I decided to catch up on the qualifications necessary for university entrance, to first start studies in Geography and finally to become a doctoral researcher. In the meantime, I started a family and my son grew up and became a young man. All of this was possible without respect to income or origin. Isn't it a luxury? Yes, it is and I don't want to take it for granted. Such a course of life would not be possible for most people in this world. This is why I am grateful and humble. And I wish I can give something back in the future in some way or other.

Many thanks to all my helpful friends and colleagues who became friends, especially in the exciting last weeks before submitting this doctoral thesis. Special thanks to those who neglected their own work to give me a helping hand. I don't want to list names here. Such a list could never be complete. However, I feel the need to acknowledge my very patient doctoral supervisor Tobias Kümmerle, who was extremely engaged to bring me to this point. Thanks a lot!

Abstract

Ongoing population growth, changing diets, and a rising demand of bioenergy will require an increase in agricultural production. Beside agricultural expansion, with its known consequences for natural ecosystems, intensifying agricultural production is another pathway to meet increasing demands. However, our understanding of spatial patterns of agricultural land use in general, and land-use intensity in particular remains weak. This is because consistent data sets are not available, especially at broad geographic scales. Europe is as a prime example for a large region that is undergoing both, intensification as well as decreasing agricultural land use. The overarching goal of this doctoral thesis was twofold: the first goal was to develop methodologies that allow for consistent mapping of land-use intensity by combining time series of the Moderate Resolution Image Spectroradiometer (MODIS) Normalized Differenced Vegetation Index (NDVI) from 2000 to 2012 and agricultural statistics. The second goal was to map spatial patterns of land-use intensity, concerning cropland and grassland management systems across Europe. To assess land-use intensity, a wide range of intensity indicators were mapped, by using a suite of advanced algorithms including Random Forest classification, Spline Analysis of Time Series (SPLITS), and Self-Organizing Maps (SOMs). Overall, the resulting maps revealed distinct spatial patterns of land-use intensity with high-intensity areas in Western and Central Europe and the Mediterranean region, mostly characterized by multi-cropping, higher mowing frequency, and long crop duration. Low-intensity areas are mostly located in Eastern Europe, but also in mountain regions (e.g., Alps, and Pyrenees) and the Extremadura in Spain, where fallow and abandonment land are widespread. Agricultural abandonment is an ongoing land-use change process in Eastern Europe. At the same time, recultivation of formerly abandoned land is widespread, mainly in eastern European countries. These spatial patterns are the result of different broad-scale factors, as agro-environmental conditions, soil fertility, changes in socio-economic conditions such as the restructuring of the agricultural sector in eastern European countries after the dissolution of the Eastern Bloc in 1989, and the marginalization of farmland especially in mountain regions. The resulting maps show the potential of MODIS time series to assess the complex and multidimensional phenomenon of land-use intensity. They may form a reliable basis to assess the environmental outcomes of agricultural production and to identify target regions for sustainable intensification.

Keywords: Europe, MODIS time series, Farmland abandonment, Farmland recultivation, Land-use change, Land-management intensity

Zusammenfassung

Die weltweite Bevölkerungszunahme, sich verändernde Ernährungsgewohnheiten und die zunehmende Nachfrage nach Bioenergie werden eine Erhöhung der landwirtschaftlichen Produktion erfordern. Neben der Expansion der Landwirtschaft mit ihren bekannten Auswirkungen auf natürliche Ökosysteme ist die Intensivierung der landwirtschaftlichen Produktion eine weitere Option zur Deckung des steigenden Bedarfes. Allerdings verstehen wir nur wenig von räumlichen Mustern der landwirtschaftlichen Landnutzung im Allgemeinen sowie der Landnutzungsintensität im Besonderen, da konsistente Datensätze, insbesondere über große geographische Räume fehlen. Europa ist ein Musterbeispiel für eine große Region, in der sowohl eine Intensivierung als auch ein Rückgang der landwirtschaftlichen Nutzung stattfindet. Das Ziel dieser Dissertation war zweiteilig: das erste Ziel beinhaltete die Entwicklung von Methoden, die Zeitreihen des Moderate Resolution Image Spectroradiometer (MODIS) Normalized Difference Vegetation Index (NDVI) von 2000 bis 2012 und statistische Daten kombinieren, um eine konsistente Kartierung der landwirtschaftlichen Landnutzungsintensität zu ermöglichen. Das zweite Ziel beinhaltete die Kartierung räumlicher Muster der landwirtschaftlichen Landnutzungsintensität europäischer Acker- und Grünlandmanagementsysteme. Für eine Einschätzung der landwirtschaftlichen Landnutzungsintensität wurden unter Anwendung moderner Algorithmen, wie Random-Forest-Klassifikationen, Spline Analysis of Time Series (SPLITS), und Self-organizing Maps (SOMs), eine Vielzahl von Intensitaetsindikatoren kartiert. Insgesamt zeigten die resultierenden Karten klare räumliche Muster landwirtschaftlicher Landnutzungsintensität, mit hoher Intensität in West- und Zentraleuropa und dem Mittelmeerraum, gekennzeichnet vor allem durch Mehrfachernten, hohe Mahdhäufigkeit sowie langen Anbauzeiten. Gebiete mit niedriger Intensität lagen in Osteuropa, in Gebirgsregionen (z.B., Alpen, und Pyrenäen) oder in der Extremadura in Spanien, wo Brachland und die Aufgabe landwirtschaftlicher Nutzflächen häufig sind. Die Aufgabe landwirtschaftlicher Nutzflächen ist ein aktueller Prozess der Landnutzungsveränderung in Osteuropa, während die gleichzeitige Rekultivierung ehemals aufgegebener Agrarflächen in osteuropäischen Staaten ebenfalls umfassend ist. Diese unterschiedlichen räumlichen Muster sind das Ergebnis verschiedener großräumiger Faktoren wie Agrarumweltbedingungen, Bodenfruchtbarkeit, sozioökonomische Veränderungen wie die Restrukturierung des Agrarsektors in Osteuropa nach Auflösung des Ostblocks 1989, oder auch die Marginalisierung landwirtschaftlicher Flächen, insbesondere in Gebirgsregionen. Die entstandenen Karten belegen das Potential von MODIS NDVI Zeitreihen, komplexe und multidimensionale Phänomene landwirtschaftlicher Nutzungsintensität zu erfassen. Diese könnten eine zuverlässige Grundlage bilden, Umweltfolgen der landwirtschaftlichen Produktion zu bewerten und Zielregionen für eine nachhaltige Intensivierung zu identifizieren.

Schlagwörter: Europa, MODIS Zeitreihen, Farmlandaufgabe, Farmlandrekultivierung, Landnutzungsintensität, Landnutzungsänderung

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Chapter I: Introduction

1 Land-use intensity change – causes and consequences

Land-use change presents a major driver of global environmental change and has already transformed the majority of the terrestrial surface (Ellis and Ramankutty 2007; Haberl et al. 2007). The most forceful land change in terrestrial ecosystems is the rapid agricultural expansion (Ramankutty and Foley 1998), which increasingly leads to a loss or degradation of natural ecosystems (Lambin et al. 2001). While land use provides humanity with essential food, fiber, and energy, land-use change also causes widespread negative impacts on the environment and human well-being (DeFries et al. 2004; Foley et al. 2005). Deforestation increases the CO_2 content in the atmosphere and reduces carbon sequestration in woody vegetation and soils (DeFries et al. 2002; Woodwell et al. 1983). Emissions released via land clearing, crop production, and fertilization use are also major drivers of climate change (Burney et al. 2010). Fertilization also alters major biogeochemical cycles (e.g., nitrogen) and leads to degradation of water quality (Vitousek et al. 1997). Land-use change probably will have even larger effects on biodiversity as climate change (Sala et al. 2000). Unsustainable land management results in loss of productive agricultural land due to desertification, salinization, and soil erosion (Godfray et al. 2010). The fertile land base is further diminishing as urbanization leads to the loss of prime agricultural land. At the same time, land degradation and climate change reduce agricultural productivity in many world regions. The result is widespread agricultural expansion in remaining natural ecosystems (e.g., South America and Africa) and an increasing competition among land uses for food, energy, carbon storage and conservation (Lambin and Meyfroidt 2011; Laurance et al. 2014). Moreover, as global population growth continues, land-based production will likely have to be doubled or even tripled in the next decades to satisfy humanity's rising demand for food, fiber, and bioenergy (Beringer et al. 2011; Erb et al. 2013; Krausmann et al. 2013). Changing food preferences, such as the higher demand for ruminant meat and milk products, will further increase the pressure on existing agricultural systems (Kastner et al. 2014).

Global land use is thus not sustainable at present and reducing the environmental impact of land use and increasing the agricultural production substantially is a central challenge of the 21st century (Erb et al. 2009; Foley et al. 2011). How this challenge can be achieved remains unclear (West et al. 2014). A step towards this could be the sustainable intensification of existing agricultural land (Foley et al. 2005; Lambin and Meyfroidt 2011). Sustainable intensification aims to produce more food from the same area of land while reducing the environmental impact of land use (Beringer et al. 2011; Godfray et al. 2010). This can be achieved by reducing waste and improved land management practices to close yield gaps and increase cropping frequency (Foley et al. 2011). How to achieve such a sustainable intensification of existing land production systems is a major issue for future research (Rounsevell et al. 2012).

2 Land-use intensity in Europe

While agriculture expands into remaining undeveloped fertile land in many world regions, in temperate zones abandonment and reforestation have become widespread (Lambin et al. 2013; Meyfroidt and Lambin 2011). This is partly reasoned by increasing yields due to fertilizer application, the development of new technologies, as well as increasing agricultural imports from other worlds regions, conservation policies, and structural changes in agriculture (Ellis et al. 2013; Kastner et al. 2011; Rounsevell et al. 2012). Europe for example, achieved most of the additional agricultural production of the last 50 years through intensification, whereas agricultural areas remained largely stable (Rounsevell et al. 2012; Rudel et al. 2009) (Figure I-1). Europe is characterized by a wide range of agricultural systems pertaining to forestry, grassland, and cropland with very different degrees of land-use intensity (Herzog et al. 2006). These highly diverse agricultural systems, ranging from traditional to agri-business farming, are the result of the large environmental, political, and socio-economic heterogeneity across Europe (Jepsen et al. 2015; Vos and Meekes 1999). The typical European cultural landscapes, characterized by high aesthetic value, rich cultural heritage, and high farmland biodiversity, are the result of a long agricultural history (Angelstam et al. 2003; Poschlod and Bonn 1998; Stoate et al. 2009). Furthermore, after World War II until the dissolution of the Eastern Bloc (former USSR-aligned countries) in 1989, Europe experienced two different economic systems: the capitalistic, market-driven economy in Western Europe, and a state-command (planning) system in Eastern Europe. The legacy of these different agricultural systems is still visible today in the spatial land-use and land-cover patterns, which show a distinct east-west divide across Europe (Lerman 2004; Niedertscheider et al. 2015). In many regions of Eastern Europe, intensification started later and developed at a slower rate compared to Western Europe, indeed, some areas still have not reached the level of agricultural industrialization of Western Europe (Jepsen et al. 2015; Rozelle and Swinnen 2004). The subsequent transition from state-command to market-driven economies after the dissolution of the Eastern Bloc led to massive changes in the agricultural sector with widespread farmland abandonment (Alcantara et al. 2013; Baumann et al. 2011; Kuemmerle et al. 2008; Prishchepov et al. 2012a) and drastic declines in crop yields and livestock numbers (Rozelle and Swinnen 2004). Abandonment occurred also in mountainous regions (Gellrich et al. 2007; MacDonald et al. 2000) and in the Mediterranean as a result of rural depopulation, abandonment of traditional farming practices, water scarcity, and soil degradation (García-Ruiz and Lana-Renault 2011; Svetlitchnyi 2009). But also land-use policies such as the EU's set-aside schemes removed agricultural land from production (Tscharntke et al. 2011). Altogether, these different historic, socio-economic and environmental conditions led to various mosaics of land-use intensity all over Europe. Therefore, Europe is a prime example to study different levels land-use intensity and intensification processes. The current spatial patterns of land-use intensity are poorly understood and European-wide, observation based land-use intensity maps at scales fine enough to inform land use and conservation planning currently do not exist. Consequently, it is important to develop tools allowing to map changes in land-use intensity in space and time (Kuemmerle et al. 2013; Mustard et al. 2004; Verburg et al. 2010).

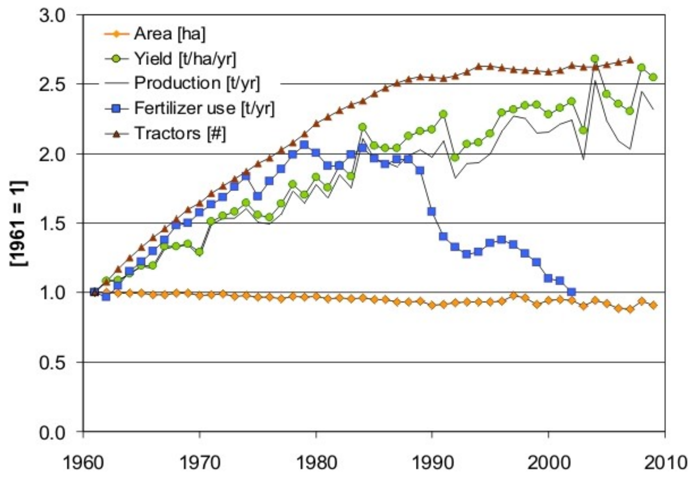

Figure I-1: Change in cereal production, cropped area, and yield; and the trends in fertilizer application and agricultural machinery use in the EU-27 countries from 1961 to 2009. Whereas the extent of cereal cultivation decreased over this period, cereal production more than doubled, due to yield increases of a similar magnitude (Rounsevell et al. 2012).

3 Mapping land-use intensity and the role of remote sensing

Whether at global or European scale, we know little about patterns of current land-use intensity and intensification pathways in agriculture systems (Kuemmerle et al. 2013). In the vast majority of cases, a comprehensive assessment of Europe’s land-use intensity and intensification processes is not feasible due to lack of adequate data sets. Existing maps are either local in extent, based on model outputs instead of observations, are too coarse in scale (e.g., national statistics), or represent only snapshots in time which cannot describe highly dynamic land management systems (Kuemmerle et al. 2013; Siebert et al. 2010b). This may be one reason why land-use science as a research discipline has mainly focused on conversion processes among broad land-cover classes (i.e., cropland, grasslands, and forests). Methods for capturing changes in management intensity have received much less attention (Foley et al. 2011; Lambin et al. 2001; Temme and Verburg 2011; Verburg et al. 2010). This is problematic because land-use intensity changes are at least as widespread as land conversions, especially in developed regions (e.g., Europe). However, existing land-use intensity maps are not adequate, in particular due to a lack of input data, especially at broader geographic scales. Another important reason for the lack of adequate data sets is the multidimensionality of land-use intensity, meaning that often a range of metrics are needed to map land-use intensity (Erb et al. 2013). Kuemmerle et al (2013) provide an overview of quantitative, spatially explicit metrics of land-use intensity, and propose to map land-use intensity along the dimensions of (1) input, (2) output, and (3) system properties (Kuemmerle et al. 2013) (Figure I-2). Input metrics measure, for example, fertilizer application rates, cropping frequency, land and labor ratios or rotation lengths. Output metrics relate outputs from the production system to inputs, for instance, yields, capital productivity or residue/felling ratio in forestry. System metrics relate the inputs or outputs to land based production to system properties and measure, for example, yield gaps (actual vs. potential yield) or human appropriation of net primary production (HANPP).

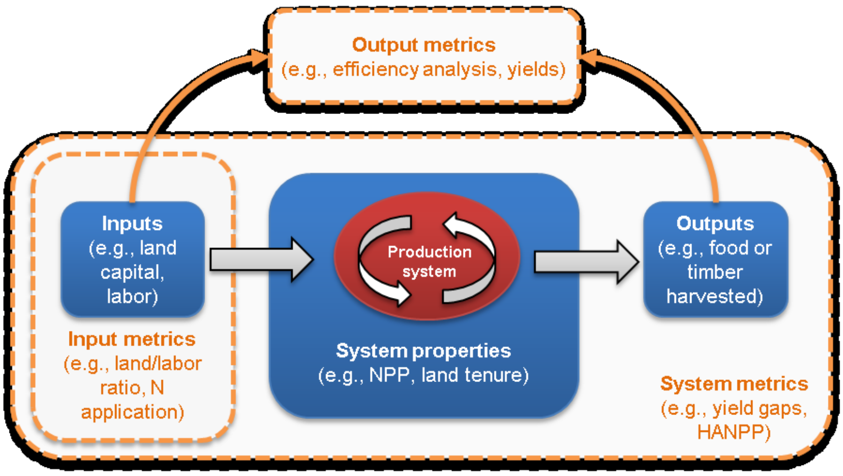

Figure I-2: Schematic overview of land-use intensity metrics. Metrics (orange boxes) are quantitative, spatially explicit measures of land-use intensity derived by relating different dimensions to each other (e.g., fertilizer/land, labor land) (Kuemmerle et al. 2013).

Remote sensing has the potential to contribute to the suite of metrics for land-use intensity. However, in the past land-use science has strongly focused on land cover (e.g., forest cover) and conversions therein (e.g., deforestation and urbanization), whereas remote sensing of land-use intensity remains scarce (Kuemmerle et al. 2013; Siebert et al. 2010b). This is partly because changes in land-use intensity often result in gradual, subtle changes in land cover, which can be hard to capture using the spectral information of satellite images. Such subtle spectral changes are often difficult to distinguish from background variability introduced by phenology, atmospheric, or topographic effects (Kuemmerle et al. 2013). In order to contribute to the development of land-use intensity metrics, a remote sensing data set has to fulfil three basic requirements: (1) it has to be available across broad geographic scales, (2) the spectral resolution, and (3) the temporal resolution needs to be high enough to detect different vegetation types and subtle spectral changes in the vegetation cover.

Medium-resolution satellite sensors, such as the Moderate Resolution Imaging Spectroradiometer (MODIS), Visible Infrared Imaging Radiometer Suite (VIIRS), or Satellite Pour l'Observation de la Terre (SPOT) VEGETATION, provide consistent data for assessing and mapping land-use intensity at broad scale (Gobron et al. 2005; Rogan and Chen 2004; Siebert et al. 2010b). In particular, a MODIS time series may be particularly suitable to contribute to the mapping of land-use intensity. The MODIS sensors on board the carrier satellites Aqua and Terra provide the longest times series (2000-present) of moderate spatial resolution satellite imagery (~232 m). The daily temporal resolution furthermore allows capturing the current state and seasonal-to-decadal dynamics in land-cover properties (e.g., land surface phenology, seasonal scale fluxes of water, energy, and carbon) (Friedl et al. 2010; Ganguly et al. 2010). As the length of the MODIS time series continues to grow, new opportunities arise for more accurate assessments of gradual changes in land cover, and thus potentially land-use intensity. MODIS data allow for more input metrics of land-use intensity, for example, the extent of agricultural land use and fallow (Alcantara et al. 2013; Pittman et al. 2010), the cropping frequency (de Beurs and Ioffe 2013), the number of harvests per year (Biradar and Xiao 2011; Li et al. 2014; Sakamoto et al. 2009; Spera et al. 2014), and the length of the cropping season (Siebert et al. 2010b). There have also been made advances in the challenging mapping of grazing intensity (Hickler et al. 2012; Kawamura et al. 2005; Ritchie 2014) and in mapping irrigated and rainfed agriculture (Ozdogan and Gutman 2008; Ozdogan et al. 2006; Salmon et al. 2015). Output metrics can also be captured, for example, by identifying the rate of forest harvested (Jin and Sader 2005) or yield estimations (Fang et al. 2011). Finally, MODIS data allow for capturing system-level metrics, for example, the growing stock and above-ground biomass in forests (Gallaun et al. 2010) or the gross and net primary production (Zhao et al. 2005). These studies exemplify the potential of MODIS time series to map indicators of land-use intensity. However, the potential of satellite based, broad scale land-use intensity indicators are not been fully explored. Therefore, exploring the potential of MODIS time series to generate metrics allowing for the characterization of land-use intensity is one of the primary goals of this doctoral thesis.

4 Thesis design

4.1 Objectives

Using Europe as an example the overarching goal of this doctoral thesis is to deepen the understanding of land-use intensity patterns in agricultural management systems. The methodological backbone of this work is the analysis of MODIS NDVI time series across European cropland- and grassland management systems. The two major contributions of this work will be: (1) the development and mapping of a wide range of land-use intensity metrics combined with agricultural statistics, and (2) the identification and characterization of spatial patterns and similar regions of cropland- and grassland management systems. Specifically, this work aims to answer the following overarching research questions:

1. *How can the measuring and mapping of land-use intensity be improved using MODIS NDVI time series?*
2. *What are the spatial patterns of land-use intensity and what are regions of similar agricultural management systems across Europe?*

This doctoral thesis is structured in three core chapters (II-IV) and each addresses further independent research questions. Figure I-3 provides a conceptual overview of the different intensity indicators, indices and clusters of similar agricultural management systems and their derivation.

4.2 Research Questions

Research questions Chapter II

1. What are the yearly extent and spatial patterns of fallow and active farmland across Europe from 2001 to 2012?

To answer this research question, first a pre-processing chain of the MODIS Normalized Differenced Vegetation Index (NDVI) time series was applied to improve the quality of the time series. The pre-processed time series was used to develop a comprehensive training data set all over Europe. By utilizing a Random Forests classifier, annual and European wide active/fallow maps from 2001 to 2012 were derived. The validation of these maps based on independent observations from the Land Use/Land Cover Area Frame Survey (LUCAS), and where LUCAS data were not available, on dense time series of Landsat TM/ETM+ images, and high-resolution images available from Google Earth. The annual fallow/active maps were further used to develop land-use intensity indicators.

2. What are the total area and spatial patterns of farmland abandonment and recultivation across Europe?
To answer this question the active/fallow maps were used to derive the fallow frequency (i.e., total number of fallow years within the observation period) and to develop different definitions of farmland abandonment and recultivation of former abandoned farmland. This was done by comparing the two periods 2001 to 2006 and 2007 to 2012 regarding the share of active and fallow observations. Then, significant hotspots of abandonment and recultivation were identified by applying local indicators of spatial association (LISA). The resulting fallow frequency represents an indicator for land-use intensity, whereas abandonment and recultivation represent indicators of land-use intensity change.

Research questions Chapter III

1. What *are* the *spatial patterns of cropping intensity in Europe* from 2001 to 2012*, as measured by cropping frequency, multi-cropping*, *fallow cycles,* and crop duration ratio?
To reveal the spatial patterns of cropping intensity four cropping indicators were developed and mapped using the MODIS NDVI time series from 2001 to 2012: cropping frequency (number of cropped years), multi-cropping (the number of harvests per year), fallow cycles (recurring fallow/active periods), and crop duration ratio (the actual time under crop). While indicators cropping frequency and fallow cycles based on the annual fallow/active maps, the indicators multi-cropping and crop duration ratio based on the pre-processed NDVI time series.
2. What are regions of similar cropping systems across Europe?
This question was addressed by using the four cropping intensity indicators and self-organizing maps (SOMs) to group observations according to their similarity. Self-organizing maps are a useful tool to identify regions with similar cropping systems and reduce complexity in the multi-dimensional indicator data set. The optimal cluster number (similar cropping systems) across Europe was six.

Research questions Chapter IV

1. What are the spatial patterns of mowing on the EU's grasslands mapped from MODIS NDVI time series?

To reveal the spatial patterns of mowing across the EU's grasslands the mowing frequency was calculated (number of mowing events throughout the year) for each year of the MODIS NDVI time series using a spline analysis software (SPLITS). The robustness of this approach was tested by calculating standard accuracy metrics using data from the LUCAS surveys and determining the true positive rate compared to an expert based visual interpretation of the MODIS NDVI profile. From the mowing frequency indicator two mowing indices (MI 1and MI 2) were derived (Figure I-3).

2. How do combined metrics of mowing, fertilizer application, and livestock density determine *the* spatial patterns of grassland-management intensity across Europe?

Spatial patterns of grassland-management intensity were determined by first, calculating two combined grassland intensity indices (CGI), using the mowing index MI 1 and agricultural statistics of fertilizer application and livestock density. Second, by applying SOMs to group observations according to their similarity using the mowing index MI 1 and the data sets of fertilizer application and livestock density (Figure I-3). This resulted in an optimal number of six clusters of similar grassland management systems across Europe.

4.3 General Approach

Pre-processing of the MODIS time series

The widely used MODIS vegetation indices provide key information on phenology, land cover and land-cover change (Huete et al. 2011; Solano et al. 2010). The three core chapters based on analyzing a MODIS NDVI time series from the satellites Aqua (MYD13Q1) and Terra (MOD13Q1) from 2000 to 2012 at a spatial resolution of ~232 m. Different phenomena can lead to noise in NDVI time series (e.g., clouds, poor atmospheric conditions, or artifacts introduced by water, ice and soil background) which may affect NDVI values in the time series and cause missing values or outliers. To reduce such effects and to construct a consistent NDVI time series, a pre-processing chain was applied. The pre-processing also includes harmonization steps that consider the varying phenology, caused by the strong climate gradients across Europe (from North to South and mountainous regions). The pre-processed NDVI time series was the basis for all subsequent analysis in the individual chapters. The set-up of the pre-processing was a substantial part of Chapter II and was comprehensively presented there.

Mapping indicators of land-use intensity

All analyses of the MODIS NDVI time series based on the interpretation of changes of the phenological (temporal) profile, or more precisely, the deviation (disturbance) from a profile not in agricultural use (Figure I-4). An unmanaged or fallow field is characterized by a smooth, bell-shaped temporal profile, spectrally very similar to natural grassland. Management, such as grazing or mowing on grassland or plowing on cropland, leads to abrupt changes in the phenological profile. Managed agriculture is characterized by more irregular temporal NDVI profiles with one or more narrow peaks, with the highest peak often shifted substantially compared to the peak of natural vegetation and unmanaged/fallow land. These typical phenological features were used to first map the annual fallow and active farmland extent. From these active/fallow time series were then further indicators of land-use intensity derived (Figure I-3).

Study area

The extent of the study area varied across the three core chapter. In Chapter II and Chapter III the study area is defined by the European coverage of the land-cover map GlobCORINE. GlobCORINE is a regionally-tuned land-cover classification derived from seasonal and annual mosaics of ENVISAT's Medium Resolution Imaging Spectrometer (MERIS) from December 2004 to June 2006 at a spatial resolution of 300 m. GlobCORINE has an overall accuracy of ~90% (Bontemps et al. 2009; Defourny et al. 2010). All classes were included that could be potentially in agricultural use: ‘Rainfed cropland’, ‘Irrigated cropland’, ‘Grassland’, ‘Complex cropland’ (annual crops associated with permanent crops and complex cultivation patterns), ‘Mosaic of cropland/ natural vegetation’, and ‘Mosaic of natural vegetation’ (herbaceous, shrub, tree). Areas such as grassland and natural vegetation mosaics were also used. These areas may have been left fallow before the observation period (2000) and recultivated afterwards. In Chapter III only GlobCORINE classes containing cropland were used, specifically ‘Rainfed and irrigated cropland’, ‘Complex cropland’, and ‘Mosaic cropland/natural vegetation’. All pixels labelled as abandoned or permanently fallow based on the analyses of Chapter II were excluded (Estel et al. 2015). The study area of Chapter IV differs from Chapter II and III and is defined by the grassland extent (‘Pasture’ and ‘Natural grassland’) from the Coordinated Information on the European Environment (CORINE) land-cover product 2006 (EEA 2011). The CORINE land-cover map had to be used since the GlobCORINE product do not provide adequate grassland information in Eastern Europe. Moreover, the auxiliary data sets (i.e., fertilizer application and livestock data) were only available for the extent of the CORINE land-cover map.

Land Use/Land Cover Area Frame Survey (LUCAS)

In this work the LUCAS data base was used extensively (Eurostat 2010). LUCAS data are in-situ surveys carried out every three years since 2006 to obtain the state and dynamics of changes in land use and land cover across the EU (Delincé 2001; Gallego and Delincé 2010). LUCAS provides more than 270,000 photo-documented observation points with ground information on land cover and land management including fallow, abandoned and managed agricultural land and indirect even information on mowed and grazed grassland. This represents the largest ground-based data set on agricultural management ever collected, but so far not been fully integrated with satellite data to map land-use intensity. In this work, LUCAS data from 2009 and 2012 were used, to validate the fallow/active classification derived in Chapter II and the mowing frequency in Chapter III. To select representative validation points from the LUCAS database, the characteristics of the LUCAS survey methodology needed to be considered. To ensure the comparability between the LUCAS observations and the MODIS data, only those LUCAS points were used which fulfilled a number of conditions referring for example to the coverage of the dominant land cover within an observed field, the actual size of the field, or the distance of the LUCAS point and the MODIS pixel centroid. All points were cross-checked against high-resolution Google Earth data and the pre-processed NDVI profiles to rule out temporal mismatches or spatial misalignment.

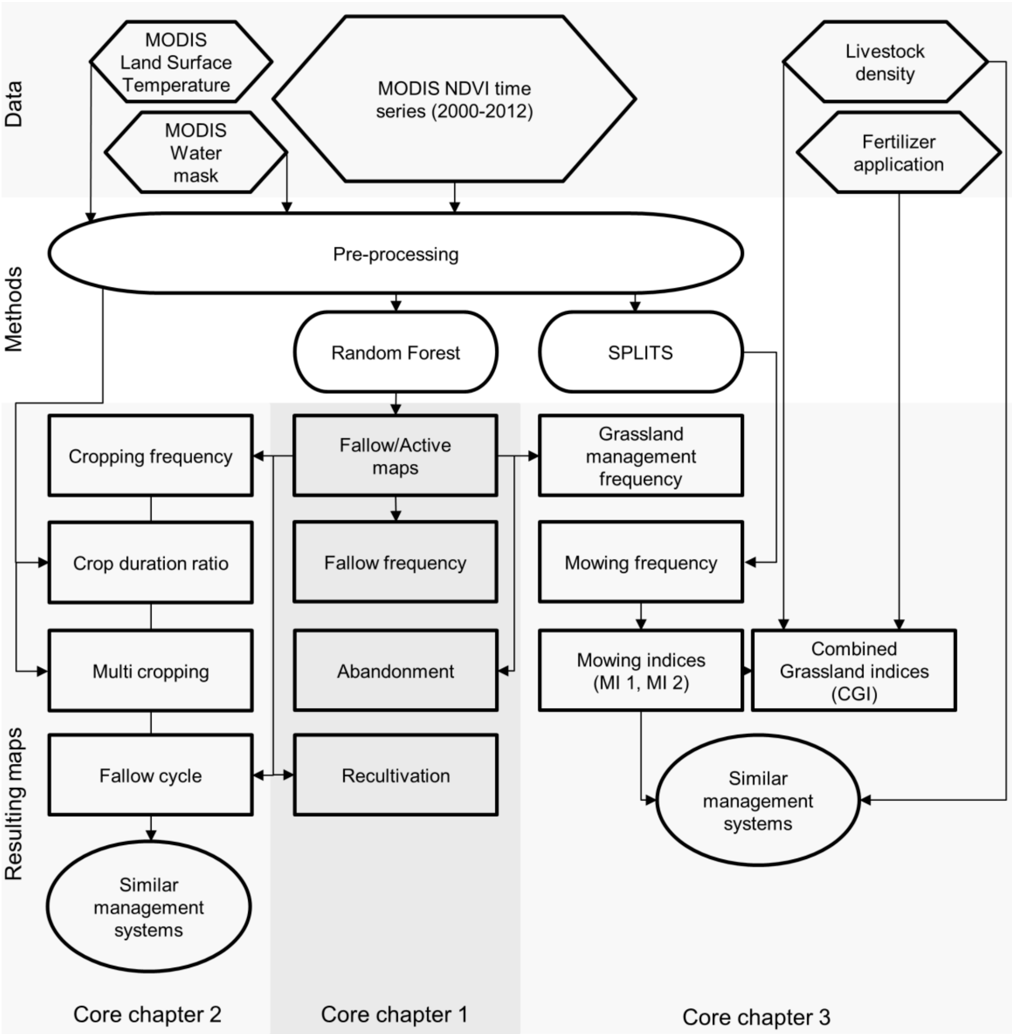

Figure I-3: Conceptual overview of data analyses.

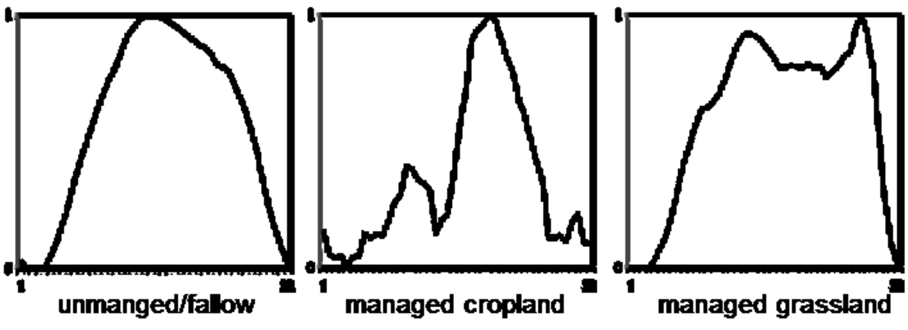

Figure I-4: Typical NDVI profiles (across one year) of unmanaged/fallow and managed agriculture, characterized by the deviation from the bell-shaped temporal profile of unmanged or fallow agricultural land.

4.4 Structure of doctoral thesis

The doctoral thesis includes five chapters. The introduction (Chapter I) is followed by three core research chapters (Chapter II-IV), and finally the synthesis (Chapter V). The core chapters (see list below) are stand-alone manuscripts, which were published (Chapter II and

III) ready to submit (Chapter IV). The Synthesis summarizes the entire work and provides a more overarching conclusion.

- *Chapter II*
  Estel, S., Kuemmerle, T., Levers, C., Alcántara, C., & Hostert, P. (2015). Mapping farmland abandonment and recultivation across Europe using MODIS NDVI time series. Remote Sensing of Environment, doi:10.1016/j.rse.2015.03.028

- *Chapter III*
  Estel, S., Kuemmerle, T., Levers, C., Baumann, M., & Hostert, P. Mapping cropland-use intensity across Europe using MODIS NDVI time series. (under review). Environmental Research Letters
- *Chapter IV*
  Estel, S., Mader, S., Levers, C., Verburg, P., Baumann M., and Kuemmerle T. Mapping grassland-management intensity in Europe by combining satellite data and agricultural statistics (In preparation for Environmental Research Letters).

Chapter II: Mapping farmland abandonment and recultivation across Europe using MODIS NDVI time series

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Abstract

Farmland abandonment is a widespread land-use change in temperate regions, due to increasing yields on productive lands, conservation policies, and the increasing imports of agricultural products from other regions. Assessing the environmental outcomes of abandonment and the potential for recultivation hinges on incomplete knowledge about the spatial patterns of fallow and abandoned farmland, especially at broad geographic scales. Our goals were to develop a methodology to map active and fallow land using MODIS Normalized Differenced Vegetation Index (NDVI) time series and to provide the first European-wide map of the extent of abandoned farmland (cropland and grassland) and recultivation. We used a geographically well-distributed training data set to classify active and fallow farmland annually from 2001 to 2012 using a Random Forests classifier and validated the maps using independent observations from the field and from satellite images. The annual maps had an average overall accuracy of 90.1% (average user's accuracy of the fallow class was 73.9%), and we detected an average of 128.7 million hectares (Mha) of fallow land (24.4% of all farmland). Using the fallow/active time series, we mapped fallow frequency and hotspots of farmland abandonment and recultivation of unused farmland. We found a total of 46.1 Mha of permanently fallow farmland, much of which may be linked to abandonment that occurred after the dissolution of the Eastern Bloc. Up to 7.6 Mha of farmland was additionally abandoned from 2001 to 2012, mainly in Eastern Europe, Southern Scandinavia, and Europe's mountain regions. Yet, recultivation is widespread too (up to 11.2 Mha) and occurred predominantly in Eastern Europe (e.g., European Russia, Poland, Belarus, Ukraine, and Lithuania) and in the Balkans. We also tested the robustness of our maps in relation to different abandonment and recultivation definitions, highlighting the usefulness of time series approaches to overcome problems when mapping transient land-use change. Our maps provide, to our knowledge, the first European-wide assessment of fallow, abandoned and recultivated farmland, thereby forming a basis for assessing the environmental outcomes of abandonment and recultivation and the potential of unused land for food production, bioenergy, and carbon storage.

1 Introduction

Agriculture has transformed large proportions of the Earth's terrestrial surface, leading to widespread loss and degradation of ecosystems and biodiversity (Ellis and Ramankutty 2007; Foley et al. 2005). Without fundamental changes in consumptive behavior, the demand for agricultural products will double by 2050 due to population growth, increasing meat consumption, and an increasing role of bioenergy crops (Beringer et al. 2011; Erb et al. 2013; Krausmann et al. 2013). Achieving production increase while minimizing the environmental footprint of agriculture is thus a central challenge for humanity in the 21st century (Foley et al. 2011; Godfray et al. 2010).

At the same time, the environmental impact of agriculture is decreasing in many world regions, especially in temperate zones where farmland abandonment and reforestation have become widespread (Cramer et al. 2008; Lambin et al. 2013; Meyfroidt and Lambin 2011). In these regions, intensification (e.g., adoption of new technologies) and structural changes in agriculture lead to a concentration of farmland in productive areas, and a decrease in farmland extent (Ellis et al. 2013; Ioffe et al. 2012; Rounsevell et al. 2012).

Abandonment can have mixed outcomes. On one hand, abandonment can lead to ecological restoration and increased carbon storage (Aide and Grau 2004; Cramer et al. 2008). On the other hand, abandonment can result in reduced water availability (Rey Benayas 2007), higher wildfire risk (Moreira and Russo 2007), soil erosion (Ruiz-Flan˜o et al. 1992; Stanchi et al. 2012), or the loss of agro-biodiversity and cultural landscapes (DLG 2005; Fischer et al. 2012; Stoate et al. 2009). When irrigation systems are abandoned, water logging and/or soil salinization can be triggered (Penov 2004). Depending on the successional stage, recultivation of abandoned land can also be very costly (Larsson and Nilsson 2005). Furthermore, farmland abandonment in Europe may lead to a displacement of land use to regions outside Europe, such as Southeast Asia and South America (Kastner et al. 2011; Meyfroidt et al. 2010), with strong environmental trade-offs (Laurance et al. 2014). Recultivation of some abandoned farmland in the temperate zone could thus be an attractive option to increase agricultural production while mitigating some of the unwanted outcomes of abandonment (Johnston et al. 2011; Koning et al. 2008; Siebert et al. 2010b).

Assessing the environmental outcomes of abandonment and estimating the potential for recultivation requires maps that separate active, fallow, and abandoned farmland. However, the rates and spatial patterns of abandonment and recultivation remain poorly understood, especially at broad geographic scales (Schierhorn et al. 2013; Siebert et al. 2010b). This is not surprising, as abandonment is a heterogeneous land-use change process: driven by a mix of environmental and socio-economic factors, abandonment may lead to either a sudden or a gradual ceasing of cultivation (MacDonald et al. 2000; Prishchepov et al. 2012a; Rey Benayas 2007). Moreover, once farmland is abandoned, vegetation recovers into tall herb, shrub, or forest ecosystems, depending on climatic and soil conditions (Cramer et al. 2008; DLG 2005; Keenleyside et al. 2010).

Because of this complexity, defining farmland abandonment conceptually, and mapping it across larger areas are challenging tasks. For example, farmland fields are often considered abandoned if they remain unused for at least two to four years (DLG 2005; FAO 2014). Yet, in marginal regions (e.g., drylands) or due to agrarian policies (e.g., set-aside payments under the European Common Agricultural Policy) fallow periods of up to five years or longer are common (FAO 2014; García-Ruiz and Lana-Renault 2011; Pointereau et al. 2008). Mapping abandonment should therefore not rely on snapshots in time (e.g., maps from individual years), but rather use information on fallow and active farmland cycles over longer periods. Time series of active and fallow farmland could also serve to delineate indicators of management intensity (e.g., fallow frequency). Yet, such time series are unavailable for any larger region in the world, and methods to accurately monitor active, fallow, and abandoned farmland are lacking (Alcantara et al. 2013; Kuemmerle et al. 2013).

Medium-resolution satellite sensors, such as the Moderate Resolution Imaging Spectroradiometer (MODIS), Visible Infrared Imaging Radiometer Suite (VIIRS), or Satellite Pour l'Observation de la Terre (SPOT) VEGETATION, provide consistent data for assessing active and fallow farmland at broad geographic scales (Gobron et al. 2005; Rogan and Chen 2004; Siebert et al. 2010b). In particular, the high-temporal resolution and long lifetime of the MODIS satellites (daily coverage at the global scale) allows capturing seasonal-to-decadal vegetation dynamics at relatively high spatial resolution (Friedl et al. 2010; Ganguly et al. 2010). However, only a few studies have used these data to map fallow or abandoned farmland. For example, using a MODIS NDVI time series and a Support Vector Machine classification allowed to map of the extent of abandoned farmland for 2005 in Central and Eastern Europe (Alcantara et al. 2013). Likewise, MODIS vegetation indices were used to study abandoned farmland in Northern Kazakhstan (de Beurs et al. 2004) and the Central Great Plains of the United States (Wardlow and Egbert 2008). The cropping intensity in the Russian grain belt was mapped between 2002 and 2009 using phenological metrics based on MODIS data (de Beurs and Ioffe 2013). Finally, the global fallow land extent was estimated by integrating MODIS land-cover data into the MIRCA2000 modelling framework (Portmann et al. 2010; Siebert et al. 2010b). Although these studies highlight the potential of MODIS time series to map fallow and abandoned farmland, this ability has so far not been leveraged across larger areas.

Our main objective was to develop a methodology to capture active (managed cropland and grassland) and fallow farmland (no management) annually across Europe at the continental scale, thereby building upon earlier work to map abandonment using single-year data for a sub-region in Eastern Europe. Based on the resulting fallow/active sequences, we then calculated the fallow frequency and tested a range of alternative definitions of farmland abandonment and recultivation. We used Europe, including Eastern Europe up to the Ural mountains, as a study region because farmland abandonment has recently been widespread there (Keenleyside et al. 2010; Verburg and Overmars 2009). Abandonment is common in mountain regions (Gellrich and Zimmermann 2007; Griffiths et al. 2013; MacDonald et al. 2000) and the Mediterranean as a result of rural depopulation, abandonment of traditional farming practices, water scarcity, and soil degradation due to water and wind erosion (García-Ruiz and Lana-Renault 2011; Svetlitchnyi 2009). The EU's set-aside schemes from 1988 to 2008 also removed up to 15% of the farmland from agricultural production (Tscharntke et al. 2011). In addition, the dissolution of the Eastern Bloc (former USSR-aligned countries) triggered widespread farmland abandonment in Eastern Europe (Kuemmerle et al. 2008; Prishchepov et al. 2012a; Roques et al. 2011). While many of these lands were abandoned permanently, some have recently been recultivated, mainly due to rising agricultural commodity prices (Schierhorn et al. 2013). Yet, to date, a comprehensive assessment of the extent and spatial patterns of Europe's fallow and abandoned farmland is missing. Existing maps of abandonment or recultivation are either very local in extent (Baumann et al. 2011; Hostert et al. 2011; Kuemmerle et al. 2008; Müller et al. 2013; Prishchepov et al. 2012a; Sieber et al. 2013), snapshots in time (Alcantara et al. 2013; Alcantara et al. 2012), or based on model outputs, instead of observations (Campbell et al. 2008; Renwick et al. 2013; Terres et al. 2013; Verburg and Overmars 2009).

One reason for this paucity of continental-scale maps is the lack of adequate ground data. Europe has recently implemented a comprehensive ground observation system with the Land Use/Land Cover Area Frame Survey (LUCAS). Carried out every three years since 2006, LUCAS provides ground information on land cover and land management (Delincé 2001; Gallego and Delincé 2010; van der Zanden et al. 2013), including fallow, abandoned and active farmland. For LUCAS 2009 and 2012, for instance, around 500,000 points were surveyed and photo-documented by field surveyors in 23 (2009) and 27 (2012) EU countries

(Eurostat 2014a). This represents, to our knowledge, the largest ground-based data set on farmland management ever collected, yet these data have so far not been integrated with satellite data to map active and fallow farmland. In sum, we aimed to assess the following research questions:

1. What are the yearly extent and spatial patterns of fallow and active farmland across Europe from 2001 to 2012?
2. What are the total area and spatial patterns of farmland abandonment and recultivation across Europe?

2 Data and methods

2.1 Satellite data

The widely-used MODIS vegetation indices provide consistent spatial and temporal information and allow analyzing terrestrial vegetation conditions across large areas (Solano et al. 2010). We used the MODIS NDVI time series of sixteen-day composites from the satellites Terra (MOD13Q1, v5) and Aqua (MYD13Q1, v5) from 2000 to 2012 at a spatial resolution of ~232 m.

Our study area was covered by 19 MODIS tiles (~123.6 Mha per tile), which together encompassing a land area of 1,040.1 Mha (Figure II-1). We also acquired the MODIS land surface temperature (LST, MOD11A2) 8-day composites of the highest-quality pixels from daily images from 2000 to 2012. The LST product provides average values of clear-sky LSTs at a spatial resolution of ~927 m (Wan 2006). We used the LST product to distinguish the winter season from the growing season (see Section 2.2). To delineate terrestrial areas in our study region, we used the MODIS land-water mask (MOD44W), a global surface water mask derived from combining the Shuttle Radar Topography Mission's (SRTM) waterbody data set with MODIS surface reflectance data (MOD44C) (Carroll et al. 2009). All MODIS data were obtained from the United States Geological Survey's Land Processes Distributed Active Archive Center (LP DAAC, http://lpdaac.usgs.gov).

To define the extent of potentially active or fallow farmland (here: all cropland and grassland) for the study area, we used the GlobCORINE land-cover map (Bontemps et al. 2009), derived via a regionally-tuned classification of seasonal and annual mosaics of ENVISAT's Medium Resolution Imaging Spectrometer (MERIS) from December 2004 to June 2006 at a spatial resolution of 300 m. GlobCORINE has an overall accuracy of ~90%

(Defourny et al. 2010) and adapts, to the extent possible, an aggregated CORINE class catalogue. We generated a mask that excluded forests, urban areas, barren land, and ice, and focused our analyses on the GlobCORINE classes rainfed cropland, irrigated cropland, grassland, complex cropland (annual crops associated with permanent crops and complex cultivation patterns), mosaic of cropland/natural vegetation, and mosaic of natural vegetation (herbaceous, shrub, tree). We included the grassland and natural vegetation mosaic classes in our mask to cover areas unmanaged in the beginning of the 2000s that could represent fallow areas and that therefore may be recultivated during our observation period (Figure II-1).

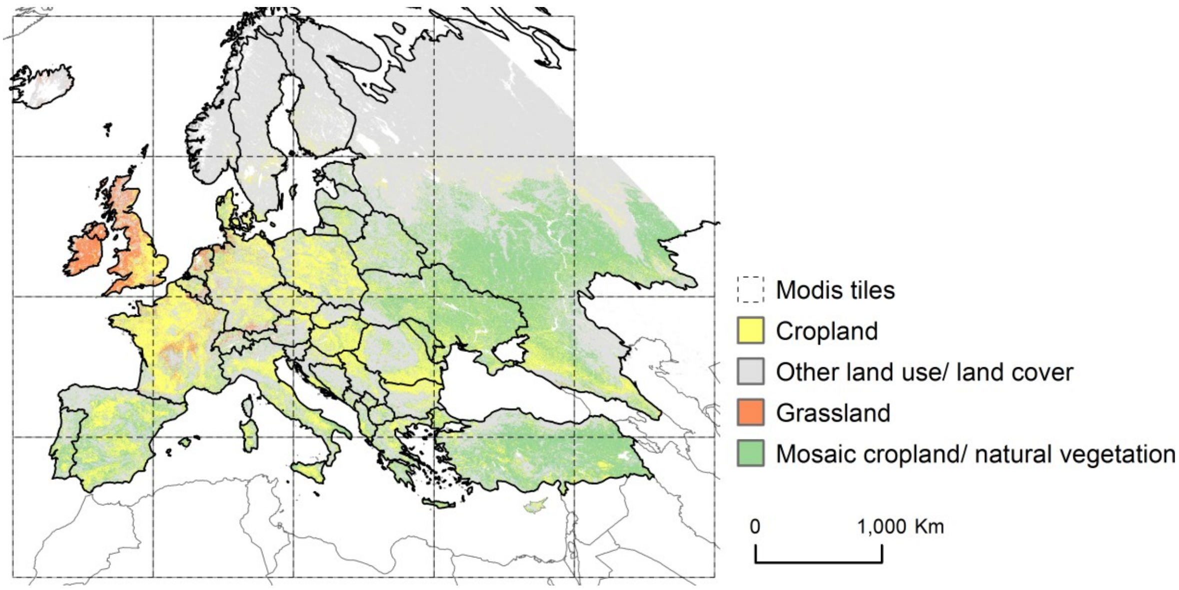

Figure II-1: Study area boundaries, consisting of 19 MODIS tiles, and the extent of potentially active or fallow farmland derived from GlobCORINE 2005/06.

2.2 Pre-processing of the MODIS time series

Clouds, water, ice, and soil background may affect the NDVI and cause missing values or outliers in time series. We applied a multi-step pre-processing chain to reduce such effects and construct a consistent NDVI time-series. First, we excluded all pixels covered with snow/ice or clouds based on the MODIS quality assurance information, using only values labelled as 'good data' or 'marginal data'. Second, we combined the NDVI time series of Aqua (MYD13Q1) and Terra (MOD13Q1) to improve the quality of the time series due to the increase of usable observations per year (Alcantara et al. 2013; Alcantara et al. 2012). Combining both Aqua and Terra time series from mid-2002 to 2012 resulted in 46 image composites per year. For the period from mid-2000 to mid-2002, when only Terra was operational, we duplicated the Terra time series. This was necessary since the software TIMESAT (Jönsson and Eklundh 2004), which we used for the time series analyses (see below), requires equally-long time series per year. Next, we further minimized the influence of residual snow and ice by excluding all pixels with a land surface temperature below 5°C (Zhang et al. 2004). For this, we used the MODIS land surface temperature (LST) time series from the MOD11A2 product. The LST time series was smoothed using TIMESAT and a double logistic fitting method (Jönsson et al. 2010). To reduce the effects of outliers and to interpolate missing values, we applied a Savitzky–Golay filter to the NDVI times series (Jönsson and Eklundh 2004). Because the year 2000 did not cover a full growing period, our time series started on 1 January 2001 and ended on 31 December 2012. Phenology varies substantially across Europe, due to the strong climate gradients (North-South, mountainous regions) and widespread irrigation in some regions (e.g., the Mediterranean). To account for this, we adjusted the phasing of the time series for all pixels where dry summers and mild, rainy winters result in a growing season from autumn to late spring in the absence of irrigation (as opposed to a growing season from spring to late autumn in the temperate region). To decide whether a pixel had such an 'inverted' growing season, we calculated for each year of the time series the average NDVI from the end of March to mid-November and the average NDVI for mid-November to mid-March and identified the two-month period with minimum NDVI over the entire year (Rötzer and Chmielewski 2001). For all pixels showing a higher average NDVI in the winter (November to March) than in the summer (March to November) as well as an NDVI minimum in the summer, we shifted the time series to start on Julian day 209 (end of July, usually the precipitation minimum), and end on Julian day 208 of the following year (Lionello et al. 2012). Since irrigation can lead to both types of profiles co-occurring in the Mediterranean, we applied the phasing for each year and each pixel of the time series individually. Since we dropped all observations below the land surface temperature threshold, the actual start and end of the growing season varied from pixel to pixel.

To further reduce complexity caused by phenological variability between regions with higher seasonality (e.g., Scandinavia) and the Mediterranean with a warmer winter season, we normalized the entire NDVI time series between the lowest value prior to the start of the growing season and the maximum value of the growing season. The resulting normalized and phased temporal profiles were then more comparable in terms of vegetation phenology than the raw spectra, and thus allowed training data collected from one area in Europe to be of use for other regions. Finally, we excluded all pixels flagged as water in the MODIS land-water mask and all pixels with an average NDVI of less than 0.1 from June to August in all years, which represent non-vegetation pixels (Zhou et al. 2003).

2.3 Mapping active and fallow farmland

For the purpose of this paper, we defined fallow farmland as land without management (i.e., not sown, cropped, or ploughed in the case of cropland, or not mown or intensively grazed in the case of grassland). Phenological profiles of fallow land (unmanaged cropland and grassland) spectrally correspond with natural grassland. Phenological profiles of such unmanaged farmlands are characterized by a smooth, bell-shaped temporal NDVI profile. Management, such as grazing or mowing on grassland or plowing on cropland, leads to abrupt changes in this temporal profile. Active farmland is therefore characterized by more irregular temporal NDVI profiles with one or more narrow peaks, with the highest peak often shifted substantially compared to the peak of natural vegetation and fallow land (Figure II-2). Intensively grazed or mowed grasslands differ from the smooth, bell-shaped fallow profiles by their plateau-shaped form, often with multiple peaks (Figure II-2). Active cropland and managed grassland also result in profiles with substantially smaller growing season NDVI integrals (i.e., area under the curve), deviating strongly from the smooth, bell-shaped profile of fallow fields (Figure II-3).

Using these phenological features, we labelled training points as active farmland or fallow farmland, by visually interpreting the phenological profile of the pre-processed NDVI time series in conjunction with high-resolution images from Google Earth. High-resolution images often show clear indicators of land management such as hay stacks, cattle or sheep herds, or irrigation infrastructure and can thus help substantially in the labelling process. To consider the environmental variability (e.g., changing land cover and climate), the varying management practices across Europe, and the unequal distribution of farmland, we used a raster grid of 80 cells, covering the majority of farmland in our study region, to distribute training sample points. We randomly selected 100 points per grid cell and masked all points outside the defined GlobCORINE farmland mask to retain around 7,000 training points. We then labelled these points as active or fallow for each year in our time series, dropping points that were not clearly identifiable. This resulted in about 5,800 independent training points distributed across Europe (Figure II-4), with per year averages of 1,026 training fallow points and 2,903 active points (Table II-1).

We used a Random Forests classifier (Breiman 2001) to derive annual active vs. fallow maps for the entire study region. Random forest classifiers are supervised machine-learners which are robust against overfitting and outliers in the training data. The Random Forests algorithm grows a user-defined number of decision trees based on the training data. The assignment of the final class labels is the majority vote of the class labels assigned by the individual decision trees (Breiman 2001; Gislason et al. 2006). The Random Forests classification was carried out with the ENMAP Box v2.0 (Rabe et al. 2014).

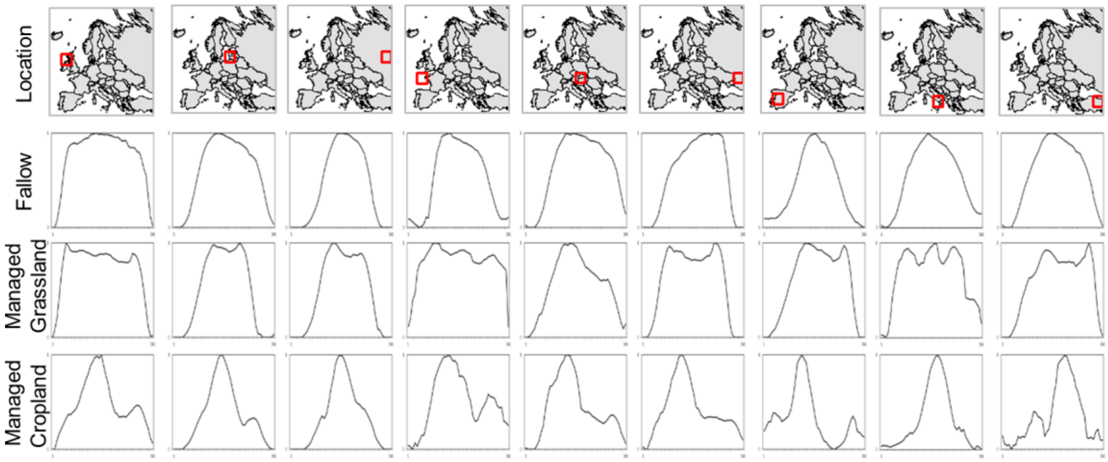

Figure II-2: Phenological profiles selected from different locations across Europe (first row) based on the 2009 LUCAS survey for fallow farmland (second row), managed grassland (third row) and active cropland (fourth row). The phenological profiles displayed here were built from the normalized NDVI time series with values between one and zero (y-axis) using 46 images from 2009 (x-axis).

Figure II-3: Averaged normalized phenological (NDVI) profile (MEAN) and standard deviation (SD) for the active and fallow classes derived from all validation and training data used in the year 2009 within the GlobCORINE cropland and grassland classes.

2.4 Validation

To validate the active/fallow farmland classifications, we gathered an extensive validation data set covering our entire study area. Our validation points were labelled based on three data sources: (1) ground observations from the LUCAS surveys implemented in 2009 (23 countries) and 2012 (27 countries), (2) dense time series of Landsat TM/ETM+ images, as well as QuickBird, IKONOS and WorldView images available via Google Earth, and (3) the MODIS NDVI profiles. For areas inside the EU, we used all three data sources, whereas for area outside the EU, where LUCAS data is unavailable, we relied on the latter two data sources (see below).

The LUCAS databases from 2009 and 2012 together contain over 70,000 survey points for fallow, unused, and abandoned farmland as well as over 200,000 points for active farmland. To select representative validation points from the LUCAS database, the characteristics of the LUCAS survey methodology need to be considered (Eurostat 2014a). We used only those LUCAS points, which fulfilled four conditions: (1) the dominant land use was either ‘Agriculture’, ‘Fallow land’. ‘Unused and abandoned areas’, but the dominant land cover was not ‘Permanent crops’, ‘Woodland’, ‘Forest’, ‘Bare land’, ‘Wetland’, or ‘Water’; (2) the LUCAS point was actually visited on the ground (i.e., visible to the surveyor); (3) the LUCAS point was located in a field larger than 10 ha, and the coverage of the dominant land cover was greater than 75%; and (4) the distance of the LUCAS point and the MODIS pixel centroid did not exceed 50 m. We then cross-checked all points against high-resolution Google Earth data and the normalized NDVI profiles to rule out temporal mismatches (e.g., cultivation after a surveyor visited a point) or spatial misalignment (e.g., surveyed field only partly within a MODIS pixel) and relabeled points if necessary (i.e., clear signs of management for points labelled as fallow, Figure II-5). We retained on average of 230 points per year for the fallow class and 1,700 points for the active class.

Validation data for areas in Central and Eastern Europe not covered by the LUCAS survey (e.g., European Russia, and Ukraine) were derived from two sources. First, we used points from Alcantara et al. (2013), who validated abandoned and active farmland using a stratified random sample of points based on abandonment classifications from a selection of 33 cloud-free Landsat TM/ETM+ footprints (Baumann et al. 2011; Griffiths et al. 2013; Kuemmerle et al. 2008; Kuemmerle et al. 2009; Prishchepov et al. 2012a; Prishchepov et al. 2012b; Sieber et al. 2013).

We used all available active cropland and abandonment points within our farmland mask. Since Alcantara et al. (2013) focused only on a single year to classify abandoned farmland, we cross-checked all points against the NDVI profiles from all other years and recent high-resolution imagery. In this way, we obtained on average 50 validation points for the fallow farmland class and 120 points for the active farmland class. Second, we selected a stratified random sample of 190 points for those areas neither covered by LUCAS nor by Alcantara et al. (2013), (i.e., parts of European Russia) and labelled these points based on Google Earth imagery and the MODIS NDVI profiles. In cases of mixed pixels (e.g., Figure II-5A and 5B), we used the high-resolution imagery available in Google Earth to identify the dominating class. As with the LUCAS points, we visually cross-checked all points against high-resolution Google Earth data and the normalized NDVI profiles (Figure II-2) to assess whether class labels had changed from one year to another and relabeled points if necessary .This yielded on average 440 validation points for the fallow farmland class and 1,870 points for the active farmland class for those areas not covered by the LUCAS survey (Table II-1).

Table II-1: Annual number of training and validation samples selected from different sources.

Year		*Training data*		*Validation data*							
		MODIS		*LUCAS*		*Landsat*		*Google Earth*		*Total*	
		Fallow	*Active*	*Fallow*	*Active*	*Fallow*	*Active*	*Fallow*	*Active*	*Fallow*	*Active*
2001		840	2927	280	1670	33	136	121	68	434	1874
2002		811	3173	186	1765	49	120	144	45	379	1930
2003		1117	2798	196	1755	80	89	163	25	439	1869
2004		1276	2768	278	1673	65	104	167	21	510	1798
2005		1161	2707	256	1695	83	86	170	18	509	1799
2006		999	3096	212	1739	61	108	162	26	435	1873
2007		970	2958	224	1727	45	124	164	24	433	1875
2008		973	3074	180	1771	41	128	174	13	395	1912
2009		1255	2761	251	1700	50	119	170	18	471	1837
2010		810	2374	266	1685	28	141	113	75	407	1901
2011		1204	2884	250	1701	51	118	148	40	449	1859
2012		932	3262	192	1759	39	130	165	23	396	1912
Mean		1029	2899	231	1720	52	117	155	33	438	1870

Using these points, we validated our fallow/active farmland maps annually and calculated standard accuracy metrics, including an error matrix as well as overall and class-wise user's and producer's accuracies. We corrected class area estimates based on map uncertainties and calculated 95% confidence intervals around area estimates (Card 1982; Foody 2002; Olofsson et al. 2013). Since our validation were derived from different sources using three random, yet slightly different sampling strategies, we also calculated accuracy measures using (a) only for the LUCAS points and (b) only the points from areas in eastern Europe outside the LUCAS survey (Belarus, European Russia and Ukraine).

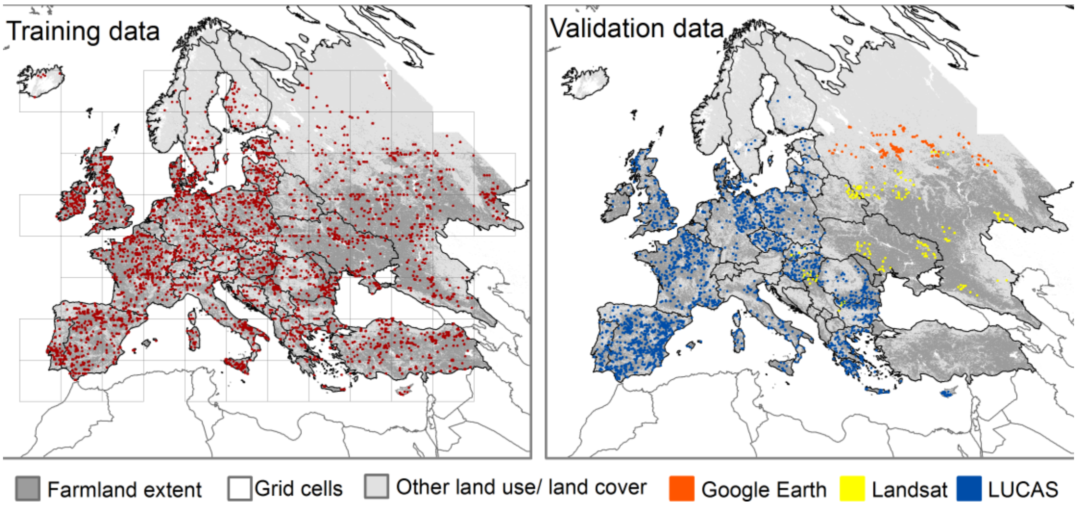

Figure II-4: The spatial distribution of grid cells used to collect the training data for active and fallow farmland with the selected training points in red (left) and the spatial distribution of validation points for active and fallow farmland colored by their source (right).

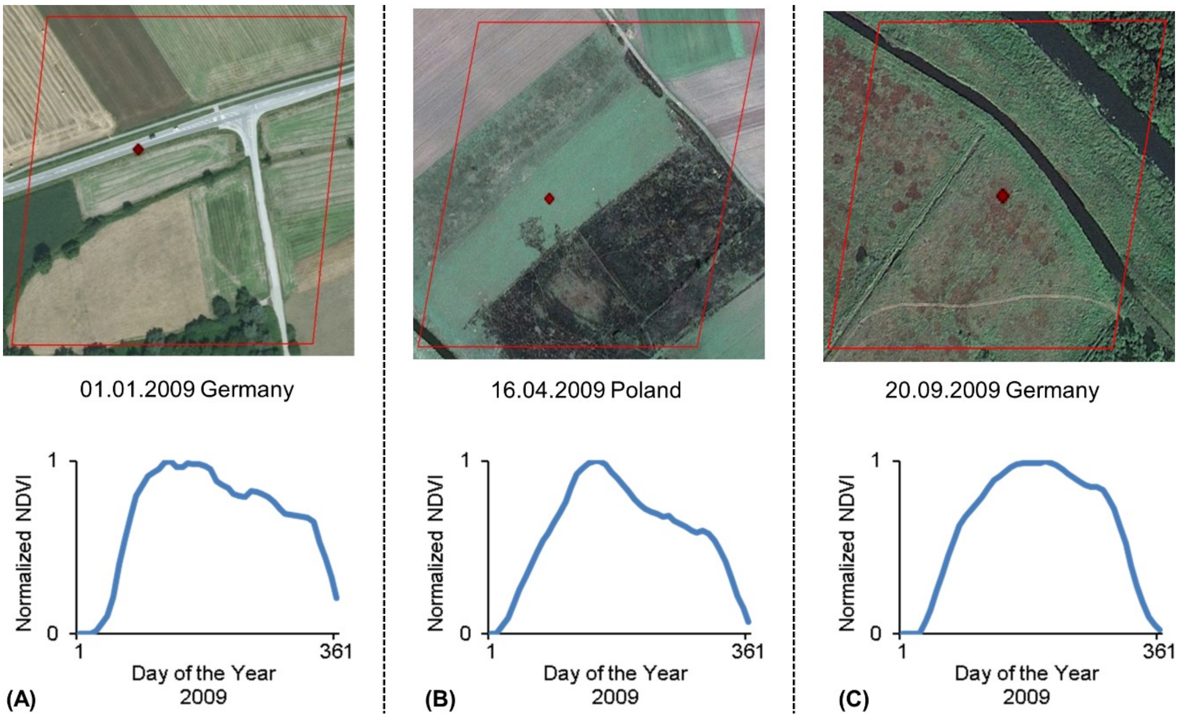

Figure II-5: Three plots (A–C) of the LUCAS survey from 2009 against the background of Google Earth high-resolution images from 2009, the MODIS pixel dimensions (red polygons), the location of the LUCAS plot within the MODIS pixel (red points), and the phenological profile of the corresponding pixel of the MODIS time series from 2009 (blue graphs). All three plots were labeled as fallow, abandoned or unused by the LUCAS surveyors but only plot C shows a typical fallow profile. Examples A and B show managed fields (cropland and grassland) within the MODIS pixel that distort the phenological profile.

2.5 Mapping fallow frequency, farmland abandonment and recultivation

Using the time series of fallow and active farmland for the period 2001 to 2012, we calculated the fallow frequency per pixel by counting how often a pixel was identified as fallow during that time. We then translated the annual land-use information into abandonment and recultivation trajectories. Definitions of farmland abandonment range from at least two to more than five years in which farmland has been unused before it can be called abandoned (DLG 2005; García-Ruiz and Lana-Renault 2011; Pointereau et al. 2008). Departing from the definition of FAO and (Pointereau et al. 2008) which used a minimum of four fallow years in five consecutive years to label a field as abandoned, we compared three alternative abandonment and recultivation definitions (D1-D3). First, we declared those pixels abandoned where we mapped five or six active years in 2001 to 2006 and five or six fallow years in 2007 to 2012 (D1). Second, we allowed for four active years in the 2001 to 2006 period (D2). A third definition allowed for only three active years in the 2001 to 2006 periods (D3). For the recultivation definitions, we applied the same rules in a reverse sequence. We declared those pixels as recultivated that had five or six fallow years in 2001 to 2006 and, alternatively, five or six active years (D1), four active years (D2), or three active years (D3) in 2007 to 2012. We defined time series with two or fewer active years between 2001 and 2012 as permanent fallow and time series with two or fewer fallow years as permanent active, respectively.

We then identified hotspots of abandonment and recultivation for all three definitions. This was done by first calculating the share of each class across a ~ 5x5-km² grid (i.e., 484 MODIS pixels) relative to the total farmland area in this 5x5-km² cell. Second, we applied local indicators of spatial association (LISA) that spatially decompose global indicators of spatial autocorrelation, in our case Moran's I (Moran 1950). Hence, LISA can be used to identify the location of spatial clusters of autocorrelation (i.e., where observations with high or low values cluster) as well as spatial outliers. We tested the significance of the detected hotspots using a one-sided *t*-test at a 5% significance level (Anselin 1995; Anselin et al. 2010).

3 Results

The Random Forests classifications resulted in 12 annual maps of fallow and active farmland spanning from 2001 to 2012. The spatial patterns of fallow farmland land were relatively stable over time but differed markedly in the area of fallow farmland mapped. Fallow farmland occurred mainly in Central and Eastern Europe and in mountainous areas (e.g., Alps, Pyrenees, and Caucasus Mountains). Active farmland was particularly widespread over the Iberian Peninsula, France, Italy, Germany, and Turkey (Figure II-6).

The annual fallow area estimates, corrected for possible sampling bias, ranged from a maximum of 163.4 Mha (2003) to a minimum of 98.7 (2011), with an average of 128.7 Mha.

Active farmland estimates ranged between 363.4 and 428.1 Mha with an average of 398.1 Mha. The 95% confidence intervals of fallow and active farmland were narrow overall, ranging from 5.8 Mha (2012) to 8.0 Mha (2003), with an average of 7.0 Mha (Figure II-7). The overall accuracy of the fallow/active farmland maps for the entire study ranged from 89% (2002) to 92% (2012). The active farmland class had a higher accuracy, with a producer's accuracy between 89% (2004) and 94% (2012) and a user's accuracy between 94% (2010) and 97% (2009/2012). The fallow class had a producer's accuracy between 76% (2001) and 90% (2003) and a user's accuracy ranged from 62% (2002) to 78% (2005). Using only validation points based on the LUCAS survey yielded an overall accuracy of 89.8%, whereas using only validation points from outside the area covered by LUCAS resulted in an overall accuracy of 87.4%. Average producer's accuracy for the fallow class was similar for both data sets (1.4% difference), whereas the averaged user's accuracy was higher (by 31.4%) in areas outside the EU compared to those areas covered by the LUCAS points (Table II-2).

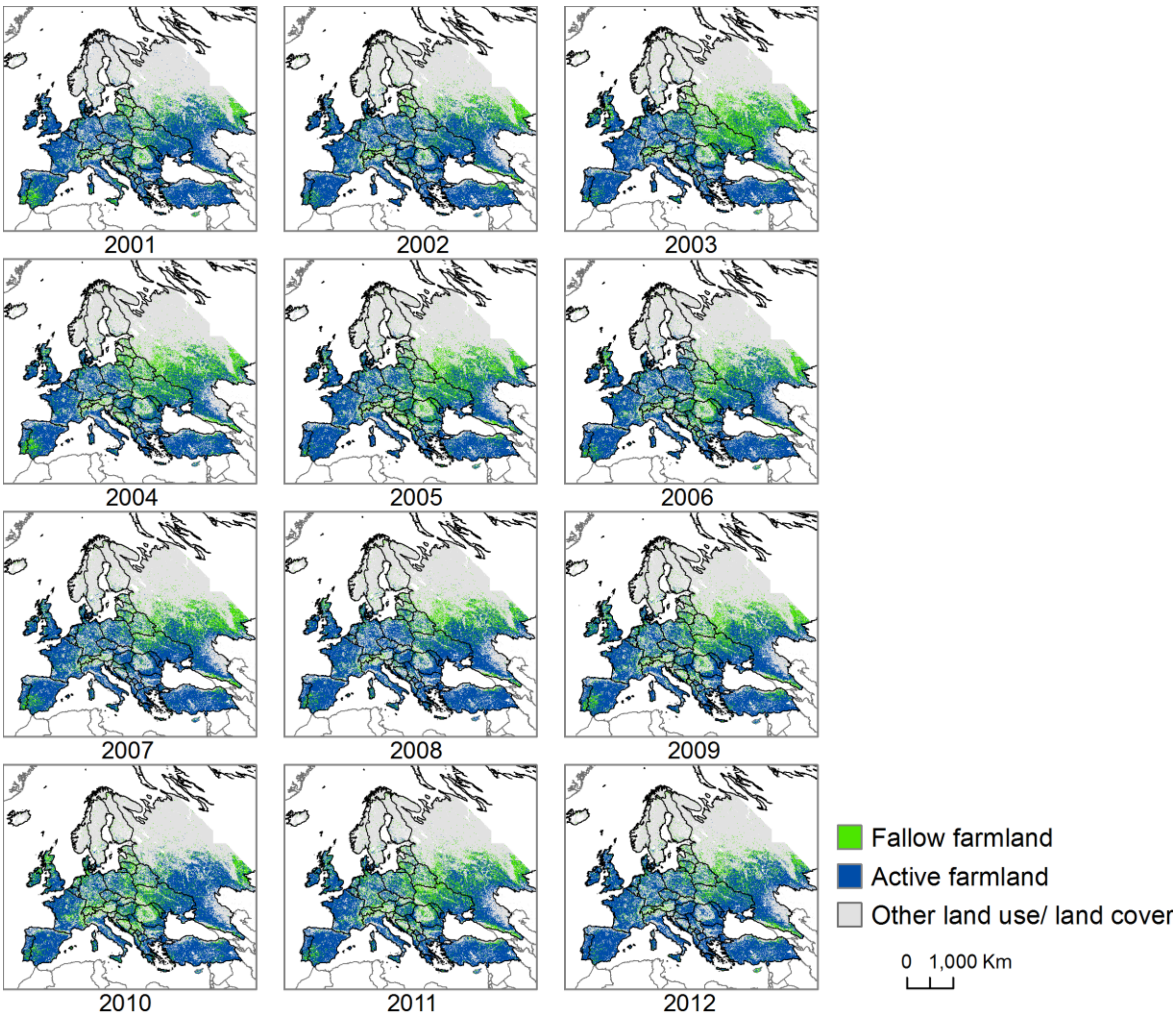

Figure II-6: Annual maps of fallow and active farmland across Europe from 2001 to 2012.

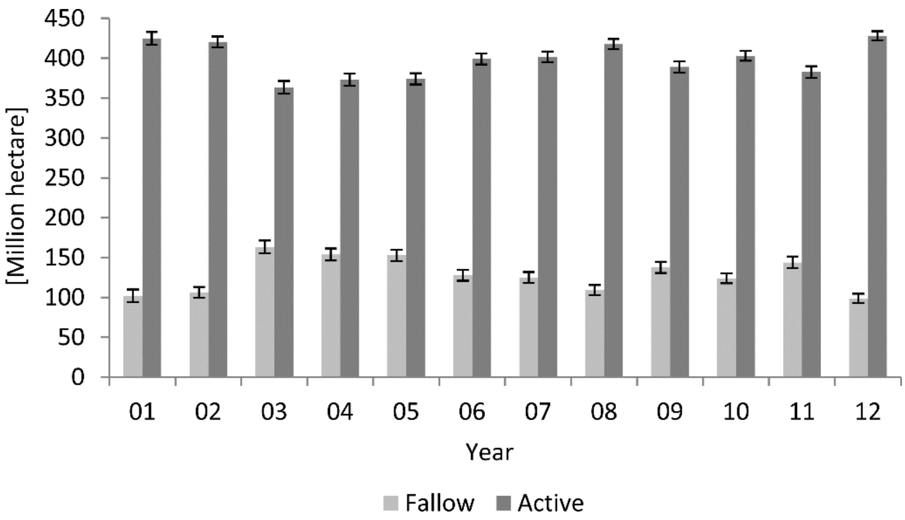

Figure II-7: Annual area estimates and their 95% confidence intervals for fallow and active farmland.

Table II-2: Producer's, user's, and overall accuracies of the annual active/fallow maps for the entire study area, for areas covered by the LUCAS survey (EU-27) and areas outside the LUCAS survey in eastern Europe (mainly Ukraine, Belorussia and Russia).

Year	*Accuracy complete (%)*					*Year*	*Accuracy LUCAS survey (%)*					*Year*	*Accuracy outside LUCAS survey (%)*				
	Producer's accuracy		*User's accuracy*		*Overall accuracy*		*Producer's accuracy*		*User's accuracy*		*Overall accuracy*		*Producer's accuracy*		*User's accuracy*		*Overall accuracy*
	Fallow	*Active*	*Fallow*	*Active*			*Fallow*	*Active*	*Fallow*	*Active*			*Fallow*	*Active*	*Fallow*	*Active*	
2001	73.0	92.4	67.7	94.0	88.9	*2001*	70.8	91.6	58.0	95.0	88.6	*2001*	68.2	95.0	86.8	86.1	86.2
2002	79.3	91.6	65.4	95.7	89.6	*2002*	72.0	91.9	49.2	96.8	89.9	*2002*	69.4	91.7	82.8	83.8	83.5
2003	86.9	91.3	80.0	94.6	90.0	*2003*	75.9	93.6	67.0	95.8	91.0	*2003*	81.5	87.7	92.5	71.7	83.6
2004	87.7	91.1	77.4	95.5	90.2	*2004*	81.4	91.7	64.3	96.4	90.1	*2004*	84.4	96.2	96.4	84.0	89.9
2005	86.8	91.6	78.7	95.1	90.4	*2005*	79.4	92.2	65.7	96.0	90.2	*2005*	79.5	94.0	94.2	79.1	86.1
2006	79.1	92.8	77.3	93.5	89.6	*2006*	70.0	92.7	64.9	94.1	89.1	*2006*	84.8	95.2	92.1	90.4	91.0
2007	82.3	92.7	76.0	94.9	90.4	*2007*	74.0	93.0	61.9	95.9	90.5	*2007*	74.8	95.0	93.5	79.5	85.0
2008	82.2	93.0	72.2	95.9	91.0	*2008*	68.8	92.4	49.1	96.5	90.2	*2008*	79.6	97.3	95.6	86.6	89.8
2009	86.8	91.1	73.4	96.1	90.2	*2009*	82.2	90.1	57.5	96.9	89.0	*2009*	80.7	96.5	95.0	85.8	89.4
2010	80.4	91.2	70.4	94.7	89.0	*2010*	82.7	88.8	65.6	95.2	87.5	*2010*	76.2	94.4	81.8	92.3	89.9
2011	83.7	91.3	76.1	94.4	89.4	*2011*	80.9	91.0	65.4	95.7	89.2	*2011*	76.6	94.4	92.7	81.1	85.8
2012	83.9	93.8	72.4	96.8	92.2	*2012*	76.2	93.3	53.0	97.5	91.7	*2012*	75.6	97.2	94.1	87.0	89.1
Mean	82.7	92.0	73.9	95.1	90.1	*Mean*	76.2	91.9	60.1	96.0	89.8	*Mean*	77.6	94.5	91.5	83.9	87.4

The fallow frequency map (Figure II-8), calculated as the sum of fallow years for each pixel across the entire time series (2001-2012), showed that fallow farmland was most frequent in Central and Eastern Europe (especially in Russia and the Baltic states), in the southern Iberian Peninsula, and in mountainous regions such as the Alps, the Pyrenees, and the Caucasus Mountains. Moderate fallow frequencies occurred in central European countries, including Germany, Poland, and Czech Republic, as well as in Ireland and the British Isles. Fallow land was less frequent in the Mediterranean region and in the Black Earth Region (i.e., Chernozem). We also used the fallow frequency to map permanently fallow areas, which occurred mainly in Central and Eastern Europe and in Europe’s mountainous regions (Figure II-8). In total, an area of 46.1 Mha of permanent fallow farmland occurred across all of Europe, of which 38.4 Mha (83.3%) was located in Central and Eastern Europe.

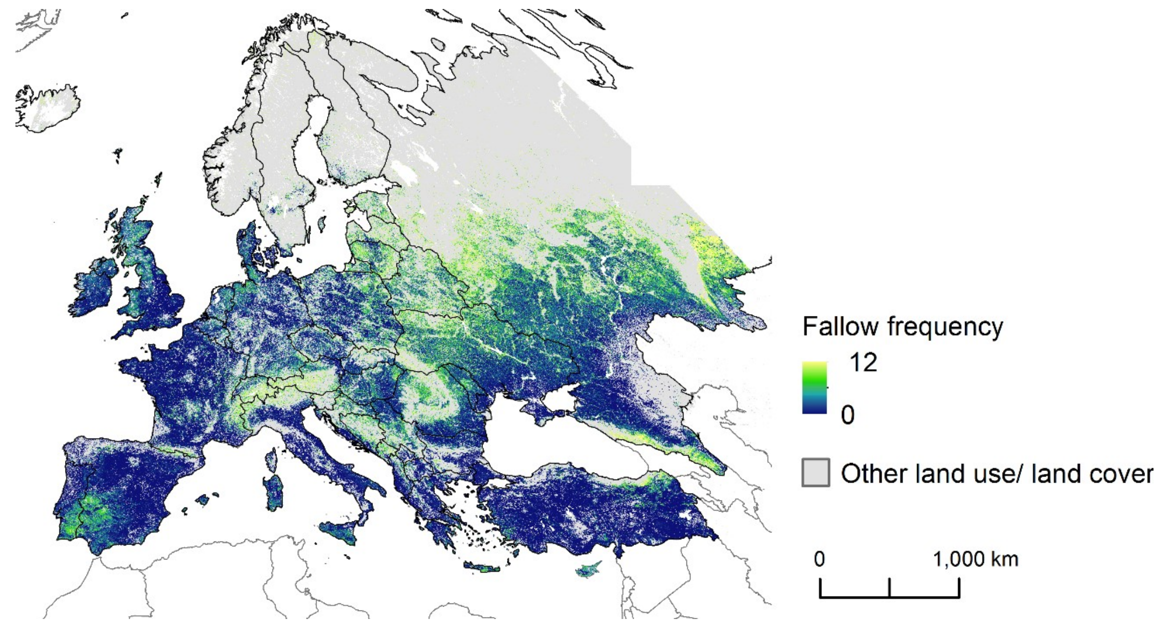

Figure II-8: Frequency of fallow years from 2001 to 2012 across Europe, where the maximum value of twelve indicates permanently fallow and the minimum value of zero indicates permanently active farmland.

Across Europe, about 333.6 Mha or 63.3% of the farmland (i.e., unmasked area) we assessed was fallow at least once and 94.7 Mha (18.0%) were predominantly fallow (seven or more fallow years) during the observation period. About 13.6 Mha (2.6%) were identified as permanent fallow (i.e., unmanaged) in our analyses. In contrast, about 193.2 Mha (36.6%) was permanently active, forming hotspots in the Mediterranean region and in agriculturally productive regions in Eastern Europe (Figure II-9).

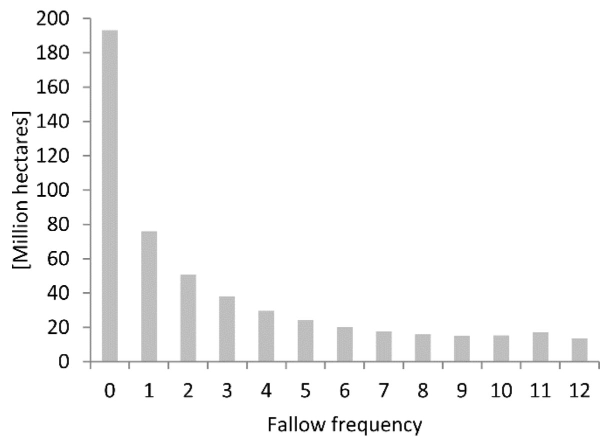

Figure II-9: Fallow frequency and the extent of permanently active areas.

The comparison among the three abandonment and recultivation definitions showed that hotspots and patterns of abandonment were quite stable across all definitions. From one definition to the next, the extent of abandoned and recultivated areas increased approximately proportionally (Figure II-10). Depending on the abandonment class definition (years of abandonment) the increase of the abandonment extent ranged from 1.1 (D1) to 3.2

(D2) to 7.6 (D3) Mha or from 0.2% (D1) to 0.6% (D2) to 1.4% (D3) of the total farmland. Major abandonment hotspots occurred in northeast Poland, Lithuania, Belarus, western Ukraine, Russia, and also in southwest Finland, and in general in many mountainous areas.

Recultivation rates of idle farmland were about 30% higher than abandonment rates after 2000 and ranged from 1.7 to 11.1 Mha (i.e., 0.3% to 2.1% of the total farmland) depending on the respective definitions. Recultivation was concentrated in Central and Eastern Europe, especially in Russia, the Baltic States, Belarus, Romania, as well as in the Balkans. In Western Europe we observed smaller recultivation clusters in Austria, Great Britain, and in the southern Iberian Peninsula (Figure II-10).

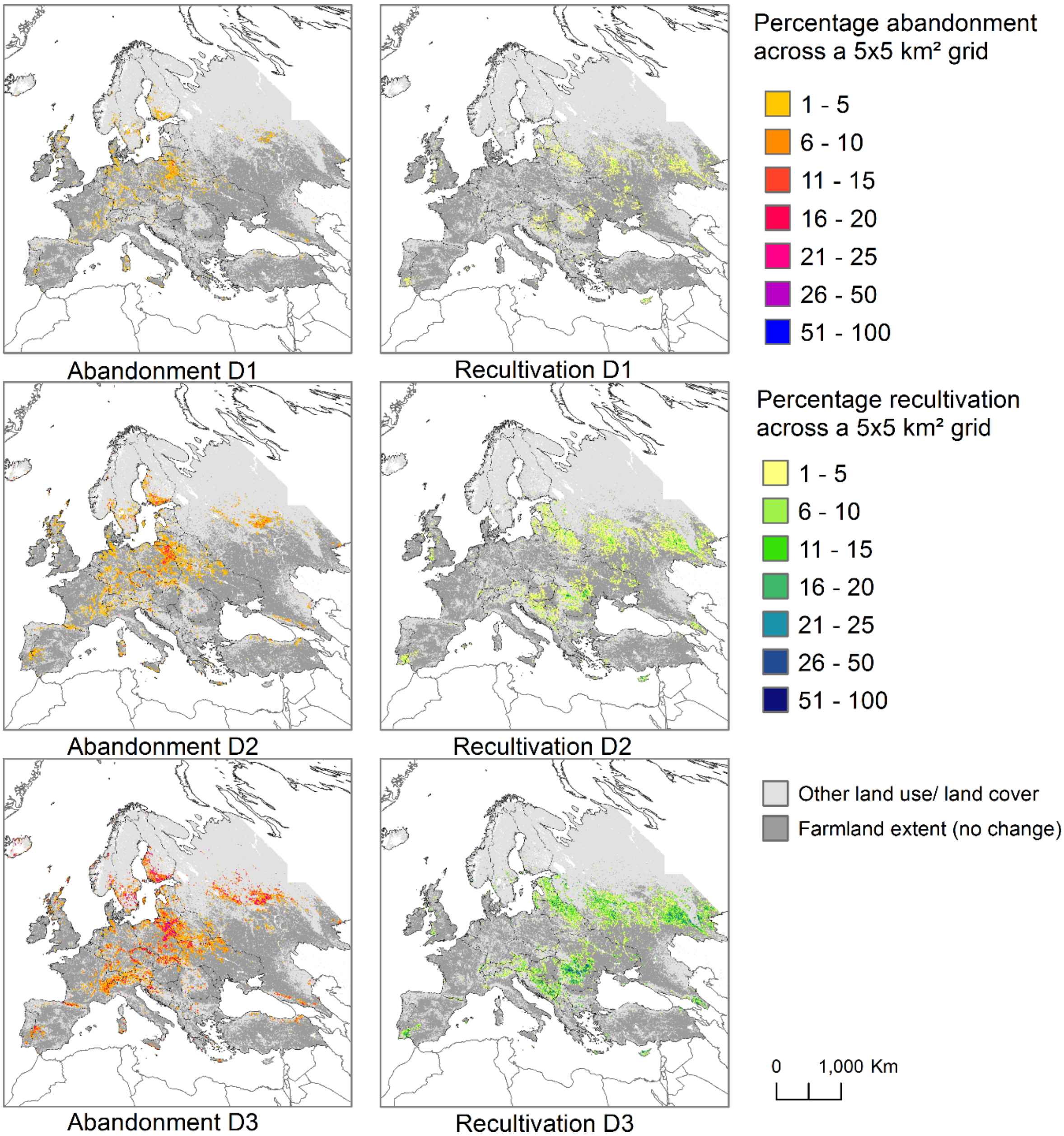

Figure II-10: Maps of farmland abandonment and recultivation corresponding to three alternative definitions based on the fallow/active time series. To visualize abandonment and recultivation patterns and hotspots, we calculated the significant hotspots and overlaid them with the proportions of recultivation or abandonment within 5 km grid cells (pixels).

4 Discussion

4.1 Mapping fallow and active farmland in Europe

Better knowledge of the extent and spatial patterns of active, fallow and abandoned farmland is important to assess the environmental and social outcomes of these land-use processes and to explore the potential contribution of currently unused lands to food and bioenergy production. We developed a methodology to derive time series of active and fallow farmland across Europe from MODIS NDVI data, which can then be used to map fallow frequency patterns, as an indicator of management intensity, as well as hotspots of abandonment and recultivation.

Our fallow and active farmland maps were plausible and agree well with previous mapping efforts for subsets of our study region, both using remote-sensing data (Alcantara et al. 2013) and land-use statistics (Schierhorn et al. 2013). Fallow frequency is an important indicator of land management intensity (de Beurs and Ioffe 2013; Ellis et al. 2013; Erb et al. 2013; Grigg 1979) and it is noteworthy that our fallow frequency patterns are in strong agreement with those from a global model based on agricultural statistics for the year 2000 (Siebert et al. 2010b). Our analyses thus highlight how indicators characterizing cropping intensity can be mapped from satellite image time series, which is a promising result given that every year, major shares of the world's cropland are fallow, e.g., 28% in 2000 (Siebert et al. 2010b), and shorter fallow cycles may allow for increasing crop yields at comparatively low environmental costs (Foley et al. 2011; Ray and Foley 2013). However, mapping fallow cycles is challenging and has, to our knowledge, not been implemented across larger regions so far. The methodology we developed here can potentially be broadly applied and can easily be updated annually, allowing for the monitoring of fallow cycles at continental to global scales. An interesting extension of the work here would be to further subdivide the active farmland class into row crops, fodder crops, permanent and pastures. While substantial ground data would be needed for such a classification, this could provide opportunities to study crop rotations and a range of other aspects related to land-use intensity (Siebert et al. 2010b).

Our analyses resulted in comparatively high overall accuracies for our fallow/active farmland maps (for a discussion of sources of uncertainty see section 4.3). We attribute the robustness of our maps to three factors: First, the availability of a large ground data set on land management (the LUCAS database), separating fallow (i.e., unmanaged) and active (i.e., managed) farmland. This ground data set also helped to attain expert knowledge in how the phenological profiles of active and fallow farmland differ, which in turn helped to expand our training data set into regions not covered by LUCAS. This allowed us to collect a large, geographically widely distributed set of training spectra for both classes. Second, we normalized our NDVI spectra to reduce the spectral complexity caused by different agro-climatic conditions and thus crop phenology (e.g., 'inverted' growing season in the Mediterranean Region; different NDVI maxima and amplitudes caused by climatic conditions) or different management practices (e.g., irrigation, andcrop types). The harmonization of key phenological parameters thus made our training data more comparable and representative across Europe, leading to a marked decrease (>15%) in commission errors of the fallow class compared to classifications using the non-normalized NDVI time series (results not shown). Third, we used a non-parametric, machine-learning classifier (random forests) that has been shown to be powerful in dealing with complex, non-normal class distributions.

4.2 Mapping of farmland abandonment and recultivation in Europe

Our study also highlighted the improved possibilities of time series approaches to map transient land-use change processes, such as farmland abandonment. Mapping abandonment is challenging due to time lags in how abandonment manifests in land cover and due to difficulties in framing abandonment conceptually. Mapping active and fallow farmland annually over decadal or longer time periods allowed for capturing time lags and for comparing alternative definitions of abandonment and recultivation. Several potentially fruitful extensions of our approach come to mind. We used relatively simple definitions of abandonment and recultivation that were based on splitting our time series in two six-year time windows, yet more complex approaches based on moving windows could be interesting to determine the timing of abandonment for longer time series (e.g., using the Landsat record). Moreover, where independent area estimates on abandonment or recultivation are available, such data could be used to identify those definitions that match such area estimates at some aggregated level.

Our analyses emphasized that farmland abandonment continued to be an important land-use change process in Europe in the first decade of the 21st century. Recent abandonment can be explained by a mixture of social, economic, and ecological factors, such as a widespread rural depopulation (Cramer et al. 2008), reduced viability of agriculture due to economic changes, decline in support for agriculture due to national and/or EU policies (DLG 2005), marginalization of farmland, especially in remote and mountain regions, and intensification of farming on more productive and accessible areas (Gellrich and Zimmermann 2007; Griffiths et al. 2013; MacDonald et al. 2000).

Abandonment between 2001 and 2012 chiefly occurred in Eastern Europe. The major hotspot found in northeastern Poland (Wschdoni and Centralny regions) corresponds to a strong decrease in goat and sheep populations as well as to a decrease in the cropland extent and total farmland area (Eurostat 2014b). We found additional hotspots of abandonment in southwest Finland, where a strong increase of extensively managed meadows and long fallows occurred from 1990 to 2005 (Keenleyside et al. 2010) and a new agri-environment scheme was introduced in 2009 to set aside 7% of the farmland (Toivonen et al. 2013). Likewise, abandonment continued to be widespread in mountainous regions (MacDonald et al. 2000).

Our map also shows large areas (46.1 Mha) of permanently fallow farmland (Figure II-7), of which 83.3% (i.e., 38.4 Mha) was located in countries of the former Eastern Bloc and former Yugoslavia. While a few of these areas likely represent natural grassland (e.g., high-mountain meadows), the major proportion likely constitutes farmland abandoned in Central and Eastern Europe after the breakdown of the communist system between 1989 and 1991, after the dissolution of the Eastern Bloc triggering changes in markets, price liberalization, ownership changes and tenure insecurity, as well as structural change in agricultural sectors (Lerman 2004; Lerman and Shagaida 2007). Although our analyses do not extend far enough back in time to assess this quantitatively, this assumption is also supported by earlier estimates of abandoned farmland of 31 Mha (Schierhorn et al. 2013). It is noteworthy that our analyses only refer to areas that were not forested in 2005 (i.e., that were included in our GlobCORINE farmland mask). While many areas abandoned after the dissolution of the Eastern Bloc have not yet reverted to forests (Cramer et al. 2008; Höchtl et al. 2005), we cannot exactly estimate the full extent of post-Eastern Bloc abandonment because our time series does not allow to map the extent of farmland before 2000 directly.

Overall, our work suggests that abandonment rates are slowing and that recultivation of formerly unused farmland has recently become an important trend. Recultivation hotspots were especially prevalent in Central and Eastern Europe, which can be explained by three factors. First, many countries in Central and Eastern Europe joined the EU in the mid-2000s (Czech Republic, Hungary, Poland, Slovakia, and Romania), providing farmers with access to production-oriented subsidies paid under the Common Agricultural Policy (CAP) as well as the Less Favored Areas payment scheme (Cooper 2006). For example, we found much recultivation in Romania, where a large area of farmland was abandoned after 1989, but put back into production after the country's EU accession in 2007 (Griffiths et al. 2013). Second, some recultivation is likely linked to the end of set-aside schemes of the CAP in 2008, which included 5-15% of all arable land in the EU (Tscharntke et al. 2011). Third, a large amount of recultivation occurred in regions of European Russia and Ukraine that have relatively favorable conditions for agriculture, where globally-increasing agricultural commodity prices have led to a reversal of post-Soviet abandonment (Schierhorn et al. 2013).

4.3 Uncertainty and limitations

We mapped fallow and active farmland annually for the period 2001 to 2012 using a large training sample, normalized NDVI time series and a non-parametric classifier, all of which likely contributed to our relatively high classification accuracies. However, a number of sources of uncertainty need mentioning. First, we used the GlobCORINE map from 2005 with an overall accuracy of ~90% (Defourny et al. 2010) to mask out all non-farmland areas, and while aggregating the GlobCORINE classes to our two target classes should have increased the reliability our farmland mask substantially, remaining uncertainty in this mask would propagate to our mapping as well. Likewise, our masking precluded mapping agricultural expansion into forest, which is very rare in Europe and was not our focus, and likely led to some permanent crops (e.g., olive groves or orchards) being masked out due to spectrally similarity with forests. Since we used a conservative mask, included all GlobCORINE classes potentially representing farmland, some of the permanent fallow we detected could also represent natural grasslands without management (e.g., alpine meadows), although such unmanaged lands are rare in Europe.Second, our classifications are likely less reliable in areas where mixed pixels dominate. Such mixed pixels occur where land-use patterns are highly heterogeneous (i.e., fields are smaller than the MODIS pixel size of ~5.4 ha). While most areas in our study are characterized by fields typically substantially larger than this, e.g., Western Europe, European part of the Former Soviet Union (Kuemmerle et al. 2013), small fields are widespread in some regions including southeastern Poland, central Romania, Albania (Hartvigsen 2014), northwestern France and southern Germany (Kuemmerle et al. 2013). This suggests that uncertainty in our fallow/active farmland maps may be spatially structured, and higher in areas with small agricultural fields (Clark et al. 2012; Ozdogan and Woodcock 2006). Unmixing fallow and active cropland at the sub-pixel level may be a promising avenue for further research in this regard. Third, our approach rests on reliably differentiating active and fallow farmland based on their phenological profiles. While this is comparatively easy for intensively managed and unmanaged farmland (Figure II-3), spectral contrast between the two classes becomes blurred for areas managed at low intensity such as pastures with very low stocking rates (e.g., alpine pastures) or dryland wood-pastures (e.g., western Spain) (Baldock et al. 1994). Active farmland could have been classified as fallow in such situations, which may explain the relatively stable moderate overestimation of fallow farmland in our results (Figure II-3). Likewise, if low-intensity management (e.g., occasional grazing) is not visible in the MODIS spectra, high-resolution imagery, or to surveyors on the ground, both training and validation data may be labelled as unmanaged, which would lead to an overestimation of the accuracy of the fallow class. Fourth, climate variability may hinder the accurate detection of fallow and active farmland. For example, in 2003 a heat wave caused a 30% reduction in gross primary productivity across Europe (Ciais et al. 2005; Gobron et al. 2005) and corresponds to the year with the highest fallow rate in our maps. Likewise, an even more drastic heat wave occurred in 2010, leading to 25% crop losses in European Russia (Barriopedro et al. 2011) and large areas of unharvested crops. Our accuracy assessment suggests that we underestimated fallow extent in 2010 (Table II-1). An explanation could come from the differences in how these heat waves occurred. In 2003, the heat wave consisted of two particularly hot periods (mid-June and beginning of August) with spring and early summer also being unusually dry. In contrast, the 2010 heat wave started in July and ended abruptly in mid-August, followed by a rainy period. The phenology of fallow areas and grassland in 2010 was thus similar to active agriculture (e.g., initial strong green-up, followed by a rapid decrease in greenness due to the drought, no harvest due to crop failure), hindering a robust separation of these classes. A future extension of our work could be to incorporate climate measures in the classification (Sulla-Menashe et al. 2011). Although outside the scope of this study, our maps provide interesting starting points to further explore how droughts influence cropland phenology as well as farmer’s reactions to drought events. Fifth, our validation data set was based on different data sources (LUCAS points for most EU countries, points from field work, Landsat classifications, and high-resolution imagery in Europe’s East). While a ground-based data set for the entirety of our study region would have been ideal, gathering such a data set is not feasible at the continental scale. Labelling points based on high-resolution imagery and the NDVI profiles only could have resulted in erroneous class labels, and we cannot fully rule out an overestimation of accuracy measures due to this. However, validation data based on higher-resolution satellite imagery are frequently used (Clark et al. 2012; Dorais and Cardille 2011; Li et al. 2014; Salmon et al. 2015) and has been shown to result in robust accuracy estimates, and may even be preferable for broad-scale studies (Cohen et al. 2010; Foody 2010; Foody and Boyd 2013; Olofsson et al. 2013). Moreover, ground data may contain labelling errors or may be challenging to upscale in space and time to compare with satellite imagery (e.g., due to mixed pixels, (Foody 2008)). Class labels may also change after a survey plot was visited (e.g., fallow field plowed later in the year) and cross-checking all validation points (i.e., 2,440 points) against the MODIS profiles helped us to weed out such errors, and to train experts into recognizing fallow and active farmland under a broad range of agro-environmental conditions. Sixth, we combined points from independently sampled data sets (i.e., raster sampling in LUCAS, stratified random sampling for the data we used for Eastern Europe). This may be problematic because some areas in Eastern Europe could be underrepresented in our data set (because the LUCAS data set was denser). Likewise, for European Russia we sampled points only within the footprints of high-resolution imagery available in Google Earth, and a potential spatial bias in high-resolution coverage would propagate into our validation data set . Combining points drawn using different sampling designs may also bias accuracy estimates, although we note that all points were drawn using random sampling. To explore the robustness of our maps, we applied separate accuracy assessments for areas covered by the LUCAS survey and for Eastern Europe outside the EU. This resulted in comparable overall accuracy, but the user's accuracy for the fallow class was 30% higher for Eastern Europe. Reasons for this may the generally larger fields in most Eastern Europe regions (especially in Russia, Ukraine, and Belarus) compared to many Western Europe (Kuemmerle et al. 2013). Furthermore, fallow land is currently much more widespread in Eastern Europe, as are abandoned former fields, as a legacy from the collapse of the Soviet Union in 1991. We also have substantial experience from prior research in all Eastern European countries. All of this suggests that our map is not less reliable in areas not covered by the LUCAS survey. Finally, LUCAS data, our own field data, and high-resolution imagery were only available for selected years (e.g., 2009 and 2012 for LUCAS). We extended the temporal cover of our validation data by interpreting the NDVI MODIS time series and multi-temporal Landsat and re-labelled points if necessary on a year-by-year basis. Spectra for the vast majority of our validation points were temporally very stable, and comparing the spectral profiles of managed and unmanaged for those years when ground visits where implemented suggested marked spectral differences between our two classes, building confidence in translating class labels back in time based on the NDVI profiles. However, we cannot fully rule out that this back-tracing approach led to mislabeling of some points (e.g., pastures grazed at low intensity as unmanaged farmland), which would nevertheless not bias our accuracy assessment unless mislabeling occurred in a systematic way.

5 Conclusion

The extent and spatial patterns of fallow and abandoned farmland are poorly understood in most regions of the world, hindering assessments of the environmental and social outcomes of abandonment, and the potential currently unused lands to contribute to food and bioenergy production. We developed a new methodology to map the extent and spatial patterns of active and fallow farmland annually at the continental scale. We also show how time series of fallow/active farmland maps can be used to derive indicators of management intensity (e.g., fallow frequency and cropping cycles) and to translate from land-use classes (fallow and active farmland) to land-use change trajectories (e.g., abandonment and recultivation). An advantage of our approach is that it also allows testing alternative definitions of abandonment and recultivation and therefore the robustness of results to potentially ambiguous definitions. Our study provides the first European-wide maps showing the spatial patterns and hotspots of active, fallow, abandoned, and recultivated farmland based on remote-sensing observations. These results confirmed that farmland abandonment continues to be a widespread land-change process in Europe, but abandonment rates have recently slowed. The recultivation of formerly unused land has become important as well, likely caused by the eastward EU expansion, EU policy changes, and the increasing demand for food and biofuel. Importantly, recultivation of unused land increasingly outweighs abandonment after 2000 in Eastern Europe. This highlights the dynamic nature of agriculture and the growing need for frequent monitoring of agricultural lands in order to assess the environmental outcomes of recultivation and abandonment, and the potential for increasing agricultural production through shorter fallow cycles. Our study shows that analyzing dense time series of satellite imagery, such as those provided by the MODIS satellites, can substantially help in addressing these issues.

Acknowledgments

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Chapter III:
Mapping cropland-use intensity across Europe using MODIS NDVI time series

Environmental Research Letter (under review)

Stephan Estel, Tobias Kuemmerle, Christian Levers, Matthias Baumann, Patrick Hostert

Abstract

Global agricultural production will likely need to increase in the future due to population growth, changing diets, and the rising importance of bioenergy. Intensifying already existing cropland is often considered more sustainable than converting more natural areas. Unfortunately, our understanding of cropping patterns and intensity is weak, especially at broad geographic scales. We characterized and mapped cropping systems in Europe, a region containing diverse cropping systems, using four indicators: (a) cropping frequency (number of cropped years), (b) multi-cropping (number of harvests per year), (c) fallow cycles, and (d) crop duration ratio (actual time under crops) based on the MODIS Normalized Difference Vegetation Index (NDVI) time series from 2000 to 2012. Second, we used these cropping indicators and self-organizing maps to identify typical cropping systems. The resulting six clusters correspond well with other indicators of agricultural intensity (e.g., nitrogen input, yields) and reveal substantial differences in cropping intensity across Europe. Cropping intensity was highest in Germany, Poland, and the eastern European Black Earth regions, characterized by high cropping frequency, multi-cropping and a high crop duration ratio. Contrarily, we found lowest cropping intensity in eastern Europe outside the Black Earth region, characterized by longer fallow cycles. Our approach highlights how satellite image time series can help to characterize spatial patterns in cropping intensity–information that is rarely surveyed on the ground and commonly not included in agricultural statistics: our clustering approach also shows a way forward to reduce complexity when measuring multiple indicators. The four cropping indicators we used could become part of continental-scale agricultural monitoring in order to identify target regions for sustainable intensification, where trade-offs between intensification and the environmental should be explored.

1 Introduction

Agricultural expansion and intensification have led to marked increases in agricultural production since World War II (Rudel et al. 2009; Tilman et al. 2002), albeit at substantial environmental costs (Tscharntke et al. 2012). Arguably, demand for agricultural products will have to increase in the future as the world's population grows, diets change, and bioenergy becomes more important (Beringer et al. 2011; Erb et al. 2013; Krausmann et al. 2013). Demand-side strategies such as reducing meat consumption and curbing food wastage (Bajzelj et al. 2014; Erb et al. 2009; Tilman et al. 2011) are promising, but will likely not be enough. How production increases could be achieved while curbing the environmental impacts of agriculture remains unclear (Butchart et al. 2010; Foley et al. 2011; West et al. 2014).

Expanding agriculture further into the last remaining undeveloped fertile lands in South America and Africa would entail drastic environmental costs (e.g., substantial carbon emissions and biodiversity loss) (Laurance et al. 2014; Licker et al. 2010; Ramankutty et al. 2002). Crop production can also be increased by intensifying agriculture on, still underperformed cropland (Godfray et al. 2010; Johnston et al. 2011). Such intensification could for example, entail an optimization of crop rotations (e.g., less fallow) and higher resource efficiency (e.g., nutrient- or water use) (Mueller et al. 2012; Ray and Foley 2013; Siebert et al. 2010b). Since the environmental impacts of intensification can be substantial (Licker et al. 2010; Matson et al. 1997), careful, context–specific assessments of the risks and opportunities of intensification are required (Garnett et al. 2013a).

Information on spatial and temporal patterns of cropland use at multiple geographic scales is required to better understand the potential for intensification. Unfortunately, existing data on cropland-use intensity are mostly coarse at scale, heavily rely on uncertain cropland maps (Fritz et al. 2011; Fritz et al. 2013), or are based on national statistics, which themselves may contain uncertainties (Verburg et al. 2011; Zaks and Kucharik

2011). Many existing datasets represent snapshots in time and cannot reflect the often highly dynamic management intensity of agricultural land (Kuemmerle et al. 2013; Siebert et al. 2010b). Substantial progress in mapping indicators of cropland-use intensity has been made recently, including yield gaps (Johnston et al. 2011; Monfreda et al. 2008; West et al. 2014), fertilizer use (Potter et al. 2010), human appropriation of net primary production (HANPP) (Haberl et al. 2012), field size (Fritz et al. 2015) or the extent of irrigated agriculture (Siebert et al. 2010a; Thenkabail et al. 2009) or tillage (Johnson 2013). Yet, our understanding of cropping patterns (i.e., temporal dynamics of cropland use), such as crop rotations, multi-cropping (i.e., number of harvests per year), crop duration (i.e., fraction of the year in which the cropland is covered with crops), cropping frequency (i.e., the number of cropped years), or the fallow land extent (Kuemmerle et al. 2013; Li et al. 2014; Portmann et al. 2010; Siebert et al. 2010b) is limited.

Dense time series of medium-resolution satellite images, such as from the Moderate Resolution Imaging Spectroradiometer (MODIS), can help identifying cropland dynamics across broad geographic extents (Friedl et al. 2010; Ganguly et al. 2010; Rogan and Chen 2004; Siebert et al. 2010b). For example, in the Russian grain belt, cropping frequency was mapped between 2002 and 2009 using phenological metrics (de Beurs and Ioffe 2013). MODIS vegetation indices allow to differentiate single, double, or triple cropping, for example in Brazil (Galford et al. 2008; Spera et al. 2014), India (Biradar and Xiao 2011), the Mekong Delta (Sakamoto et al. 2009), China (Li et al. 2014), or the mid-western United States (Wardlow and Egbert 2008). These studies highlight the potential of medium-resolution sensors to map cropping indicators, but used only single indicators over relatively short time periods to describe often highly dynamic and heterogeneous agricultural systems.

Our main goal here was to characterize European cropping systems by mapping four MODIS-based cropping indicators and by identifying typical cropping clusters. Europe is interesting for assessing patterns of cropland-use intensity for at least three main reasons. First, Europe is characterized by a wide range of agricultural systems with different degrees of cropland-use intensity caused by strong environmental and socio-economic gradients (Herzog et al. 2006; Rounsevell et al. 2012; Rudel et al. 2009). Second, Europe has a long land-use history, with most land-use change nowadays happening along gradients of intensity change. Third, Eastern Europe experienced a dramatic declined in cropland-use intensity after the breakdown of the communistic system (Kuemmerle et al. 2013; Prishchepov et al. 2012a) and is consistently highlighted as a candidate region for sustainable intensification (Foley et al. 2011; Müller et al. 2013). Therefore, Europe is a prime example to develop methods that allow capturing and mapping cropland-use intensity and changes therein.

Specifically, we assessed the following research questions:

1. *What were the spatial patterns of cropping intensity in Europe from 2001 to 2012, as measured by cropping frequency, multi-cropping, fallow cycles, and crop duration ratio?*
2. *What are regions of similar cropping systems across Europe?*

2 Data and methods

Our study area included the entire European continent and Turkey to define the cropland extent within this region, we used the GlobCorine land-cover map from 2005 (Defourny et al. 2010). To overcome scale differences between GlobCorine (300m) and the MODIS time series (231.6m), we downscaled the prior to the latter using a nearest neighbour algorithm. Based on this map we focussed on all classes containing cropland, specifically rainfed and irrigated cropland, complex cropland, and mosaic cropland/natural vegetation, and we masked all other classes (Figure III-S1 in the supplementary material).

To map cropping indicators, we used a NDVI time series pre-processed in a previous study following three steps (Estel et al. 2015). First, using satellite images from both Terra and Aqua satellites from 2000 to 2012 we reduced effects from clouds, water, snow, and ice by excluding poor-quality observations based on the MODIS quality information, land surface temperature, the land-water mask and interpolating missing values. Second, due to the strong climate gradient across Europe and the resulting varying phenology (e.g., earlier green-up and shifted vegetation peak in the Mediterranean, higher seasonality in the north), we normalized the NDVI time series to make them more comparable. The normalization was twofold and included an accounting for the shifted vegetation peak in Mediterranean environments in Europe, and harmonization the NDVI time series in regards to vegetation maxima and amplitudes across Europe. The normalization procedure is described in detail in Estel et al. (2015a). Third, we gathered an extensive training dataset on active and fallow cropland by interpreting the NDVI time series and high-resolution images from GoogleEarth, and classified each cropland pixel into active (i.e., managed) and fallow farmland (i.e., unmanaged) for each year between 2001 and 2012. The annual active/fallow maps had an average overall accuracy of >90% based on independent validation data (Estel et al. 2015).

2.1 Mapping cropping indicators

We used the pre-processed NDVI time series and the annual fallow/active maps from Estel et al (2015a) to map four cropland-use intensity indicators: (1) cropping frequency, (2) multi-cropping, (3) fallow cycles, (4) crop duration ratio at a spatial resolution of 231.6 m. To provide an intensity measurement, to better describe, and compare the mapped patterns of intensity we divided each indicator into a high, medium and low intensity class (Table III-1). We furthermore excluded all pixels labelled as abandoned or permanently fallow based on Estel et al (2015a). Our final cropland mask included an area of 400 Mha. For the indicators crop duration ratio and multi-cropping, we considered only non-fallow years.

We calculated the cropping frequency as the number of years a cropland pixel was cropped over the observation period (see supplementary material, Figure III-S2). Higher cropping frequencies thus signifies higher cropland-use intensity (Table III-1). Multi-cropping refers to the number of harvests within a single year (i.e., growing season, Spera et al. 2014). In Europe, either single or double cropping occurs. To identify double cropping, we counted the number vegetation peaks per growing season using TIMESAT (Jönsson and Eklundh 2004; Li et al. 2014), which detects double peaks based on the amplitude ratio between the primary and the secondary peak (Jönsson and Eklundh 2004). We derived annual single vs. double-cropping maps and summarized the number of double-cropped years (Table. III-1). Fallow cycles refer to recurring periods of fallow cropland. Longer and frequent fallow periods thus signify less intense land management. We defined fallow as cropland without management (i.e., not sown, cropped, or ploughed) (Estel et al. 2015). ‘Active fallow’ (e.g., cultivation of legumes for nitrogen fixation) was not considered. To identify fallow cycles, we screened the active/fallow time series for ‘chain segments’, i.e., a certain number (1, 2 or 3) of consecutive fallow years. We identified chain segments consisting of one (FC1), two (FC2), and three (FC3) fallow years between active years. We counted the occurrence of these chains across the entire time-series per pixel (see supporting material, Figure III-S3), and summarized all chain segments using a weighting scheme. Weights were calculated as the ratio of the total number of years in the time series (12) and the number of maximally possible chain segments of a particular cycle type (see supplementary material). The resulting index provides information about the level of cyclicity, and thus management intensity. We considered only time series with at least two chain segments (Figure III-3).

The crop duration ratio is the time a field is cropped in relation to the total length of the growing season (Siebert et al. 2010b). We derived the total length of the growing season as the number of days with a land surface temperature above 5°C, i.e., the time between the earliest and the latest MODIS acquisition date when plants are assumed to actively grow (Hickler et al. 2012; Zhang et al. 2004). The time period a pixel was cropped was defined as a vegetation signal of at least half the peak of the phenological curve (see supplementary material, Figure III-S4). The half-maximum is frequently used as a phenological marker for leaf unfolding and the loss of canopy structure of natural vegetation (Bradley et al. 2007; Fisher et al. 2006) and we used it as a proxy for crop green-up and harvesting. We then computed the crop duration ratio for each year and calculated the average crop duration ratio from 2001 to 2012. Since cropping cycles are more dynamic than natural vegetation (e.g., varying timing of ploughing, sowing and harvesting), we carried out a sensitivity analyses to test the robustness of our results in relation to the choice of threshold, and derived crop duration ratios for thresholds of 40%, 45%, 50% (= half-maximum), 55%, and 60%. We then calculated the standard deviation crop duration (see supplementary material, Figure III-S5).

Table III-1: Intensity classes for each indicator (low, medium, and high, based on terciles) and indicators' class share from the total cropland.

Intensity class				
	Low	*Medium*	*High*	
Cropping Frequency	1-4	5-8	9-12	
Multi-Cropping	1-4	5-8	9-12	
Fallow Cycles (Cyclicity)	0.33-0.91	0.92- 1.49	1.50-2.08	
Crop Duration Ratio	0.16-0.43	0.44-0.70	0.71-0.98	

Area share [Mha]				
	Low	*Medium*	*High*	*Total*
Cropping Frequency	20.7	72.5	306.9	400.1
Multi-Cropping	180	37.8	6.4	224.2
Fallow Cycles (Cyclicity)	77.9	26.5	4.6	108.9
Crop Duration Ratio	47.0	274.3	78.8	400.1

Area share [%]				
	Low	*Medium*	*High*	*Total*
Cropping Frequency	5.2	18.1	76.7	100
Multi-Cropping	45.0	9.4	1.6	56.0
Fallow Cycles (Cyclicity)	19.5	6.6	1.1	27.2
Crop Duration Ratio	11.7	68.5	19.7	100.0

2.2 Mapping typical clusters of cropland-use intensity

To identify similar cropping systems, we used self-organizing maps (SOMs). SOMs are an unsupervised clustering technique based on competitive learning that reduce a high-dimensional dataset to a two dimensional map by grouping observations according to their similarity (Skupin and Agarwal 2008). To identify the optimal number of clusters, we applied a sensitivity analyses with SOM clusters varying from 2 x 2 to 4 x 4 clusters (Maulik and Bandyopadhyay 2002) and used the Davies-Bouldin index that compares intra- and inter-cluster variability (Davies and Bouldin 1979) to pick the optimal cluster number. We z-transformed our indicators prior to the clustering and calculated average values across a 1x1-km^2 grid (see supplementary material Figure III-S6).

3 Results

In terms of cropping frequency, we found around 166.8 Mha (i.e., 41.7%) of all European croplands cultivated every year during 2001–2012. These areas were mainly located in western and central Europe (northern France, most of Germany, parts of England), northern Italy, eastern and northern Spain, Turkey and the Black Earth regions (i.e. Chernozem, FAO/EC/ISRIC 2003) of southern Russia and south-eastern Ukraine (Figure III-1). Around 18% of the croplands had medium cropping frequencies (i.e., 5 to 8 cropped years) and occurred mainly in the Mediterranean (e.g., Extremadura, southern Portugal) and north-western Germany (Table III-1). Around 5% of the croplands had lower cropping frequencies (i.e., 1–4 cropped years) mainly in mountain regions (e.g., Alps, Pyrenees, and Caucasus) and eastern Europe (e.g., Russia, northern Ukraine, Belarus, and the Baltics).

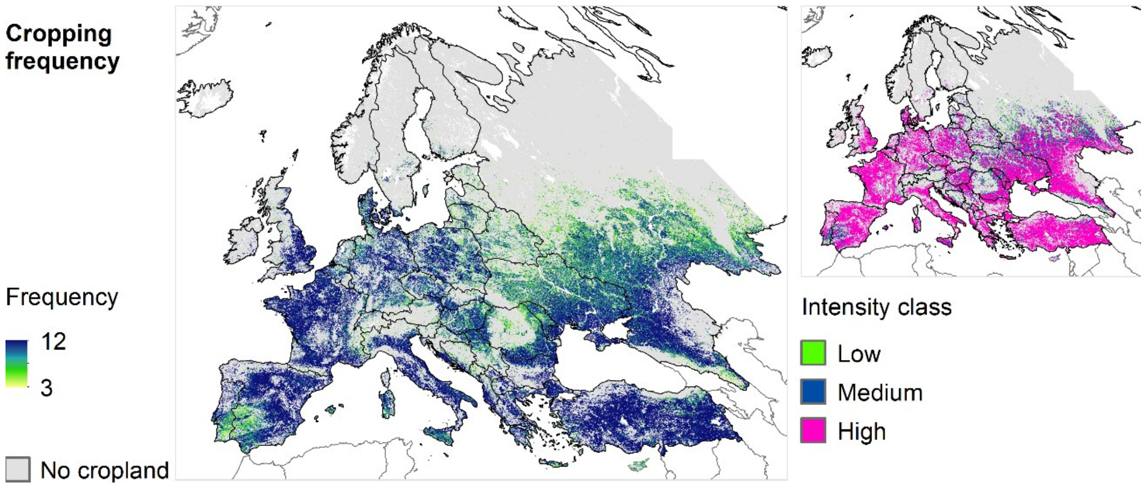

Figure III-1: Multi-cropping, defined as the number of double cropping seasons between 2001 and 2012. Low, medium, and high classes represent terciles.

Multi-cropping was widespread in the study area. About 56% (Table III-1) of all croplands in Europe were double-cropped at least once during 2001–2012. Areas where multi-cropping was high (i.e., 9-12 double-cropped years) accounted for only 2% of the total croplands, and were most widespread in central Europe (i.e., north-eastern Germany, central Poland) and Russia (i.e., Black Earth regions). Medium multi-cropping (i.e., 5-8 double-cropped years) accounted for about 9% of all croplands, mainly in central Europe, central Spain, southern Ukraine, Russia (Figure III-2).

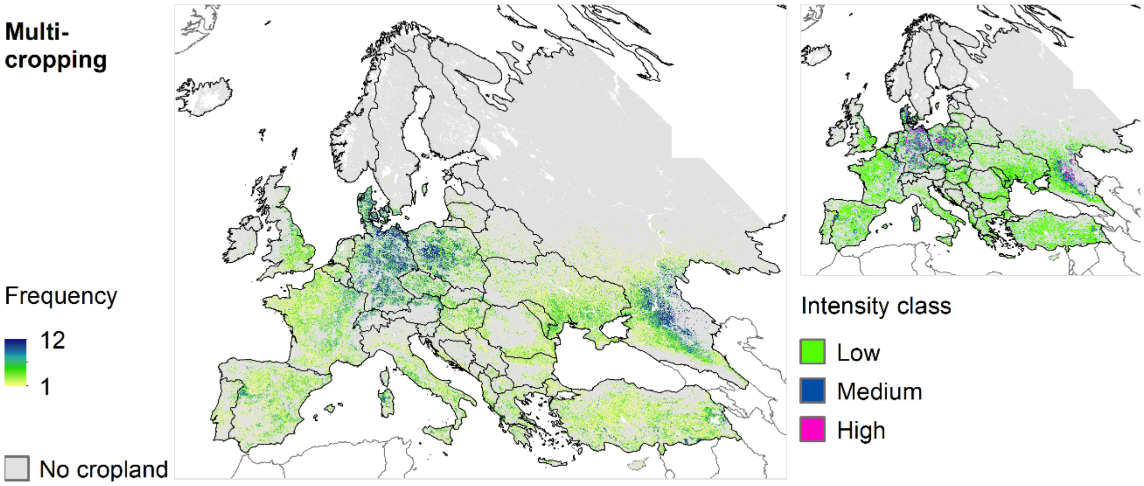

Figure III-2: Multi-cropping, defined as the number of double cropping seasons between 2001 and 2012. Low, medium, and high classes represent terciles.

Our fallow cycle mapping showed that about 27% of all European croplands had one of the three fallow cycles (Figure III-S3). Out of all croplands, about 1% had a high fallow cyclicity (upper tercile of index values) and these areas occurred predominately in the southern Iberian Peninsula, north-eastern Turkey, and Eastern Europe (Table III-1). About 26% had a medium (i.e., mid tercile) or low fallow cyclicity (i.e., lower tercile) and occurred all over Europe with concentrations on the Iberian Peninsula, Eastern Europe (i.e., northern Ukraine, Russia) and some Mediterranean areas.

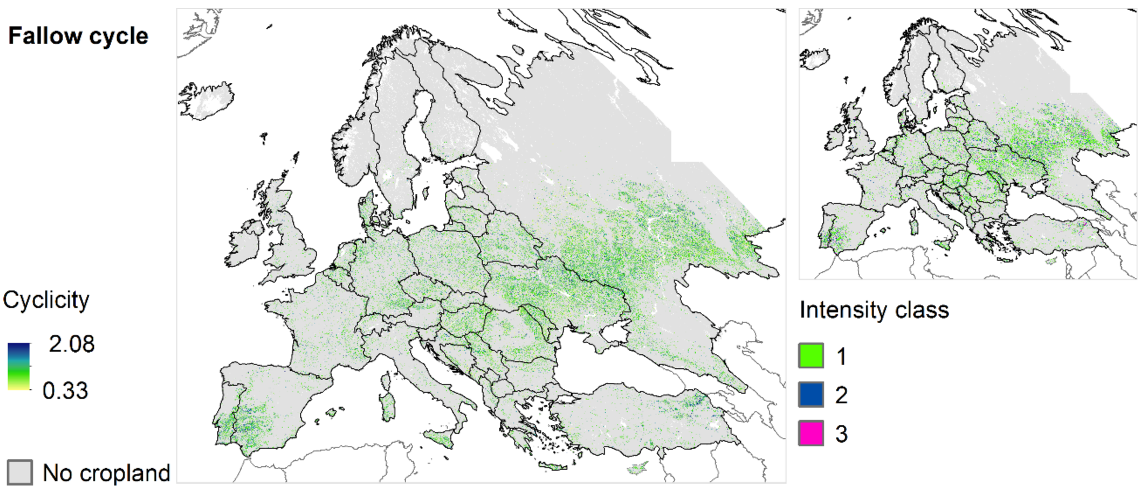

Figure III-3: Fallow cycle index (cyclicity), defined as the total number of chain segments from all fallow cycles, weighted by the maximal possible number of cycles (see text for details). Low, medium, and high classes represent terciles.

Mapping crop duration ratio (Figure III-4) revealed that about 20% of all European cropland was characterized by high crop duration ratios, mainly in central Europe (e.g., Germany, Poland, eastern France, and southern Hungary). About 69% of all croplands showed medium crop duration ratios (i.e., 0.44-0.70), occurring mainly in European Russia, Ukraine, UK and eastern France (Table III-1). A few regions (~12%) showed lower crop duration ratios (i.e., <0.43), mainly in Spain, Turkey, Italy, Greece and southern European Russia. Our sensitivity analyses showed the robustness towards alternative definitions, with standard deviations in crop duration ratio <20%. For some Mediterranean areas, where crop duration ratio is lower than elsewhere in Europe, we found a higher, but still moderate sensitivity (see supplementary material).

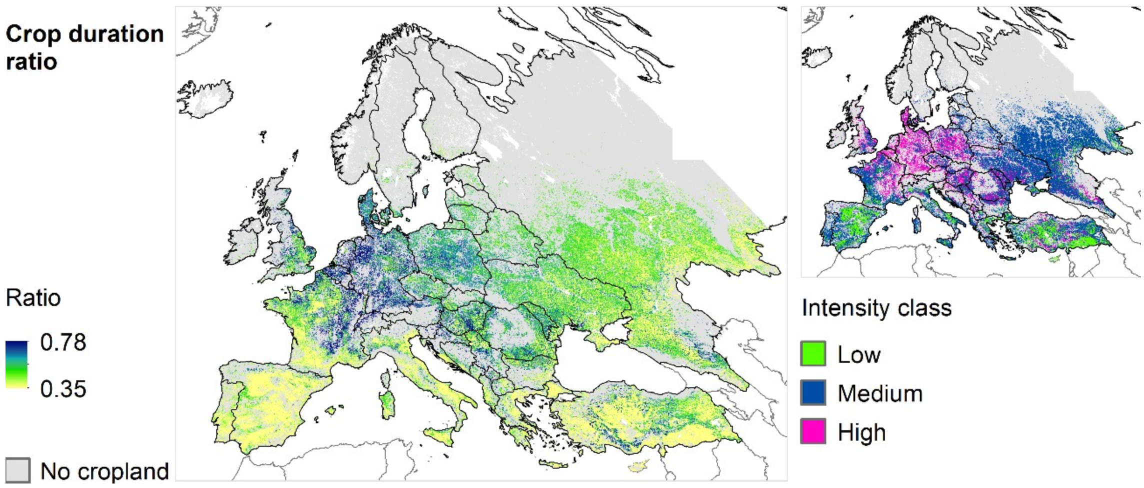

Figure III-4: Mean crop duration ratio showing the relationship between the full growing season and the time a field is under crops. High values indicate a high overlap of growing season and cropping time. Low, medium, and high classes represent terciles.

We identified six clusters of similar cropping systems (Figure III-5) using SOMs and a sensitivity analysis across varying cluster numbers (see supplementary material). To describe the magnitude and direction of the different cropping indicators in each cluster (C1-C6), we provided here the deviation (±) from mean z-score (= 0, see supplementary material, Table III-S1). Positive and negative numbers thus signify above and below average values respectively, whereas values close to zero mean that a specific indicator is close to the overall mean of the study area (Figure III-6). Cluster 1 was determined by high cropping frequencies (+0.82), crop duration ratios slightly above average (+0.22), and a very low fallow cyclicity (-1.25). This cluster occurred in northern France, England, Italy, and around the Black Sea in Romania, Ukraine, Russia, and Turkey. Cluster 2 was mainly determined by very high multi cropping (+2.76), high crop duration ratios (+0.80) and cropping frequencies (+0.72), but a low fallow cyclicity (-0.67). This cluster 2 was mainly located in Germany, central Poland, southern Russia, and western France. Cluster 3 was characterized by very low cropping frequencies (-1.78), infrequent multi-cropping (-0.80%), a marked fallow cyclicity (+0.73) and occurred mainly in eastern Europe (e.g., European Russia, Baltics, Belarus, and northern Ukraine), the Mediterranean, and in mountain areas (e.g., Alps, Pyrenees, Caucasus). Cluster 4 had very low crop duration ratios (-1.62) and a very low fallow cyclicity (-1.23), and the highest cropping frequencies (+0.85) of all cluster. This cluster occurred mainly in the Mediterranean, southern Ukraine and southern Russia. Cluster 5 was characterized by a high fallow cyclicity (+0.73), low multi-cropping (-0.53) and low crop duration ratios (-0.35). This cluster occurred mainly in Ukraine and Russia, on the Iberian Peninsula, western France, and Turkey. Cluster 6 had the highest fallow cyclicity (+0.74) and the highest crop duration ratios (+1.00) of all cluster. This cluster occurred mainly in central Europe and southern Ukraine.

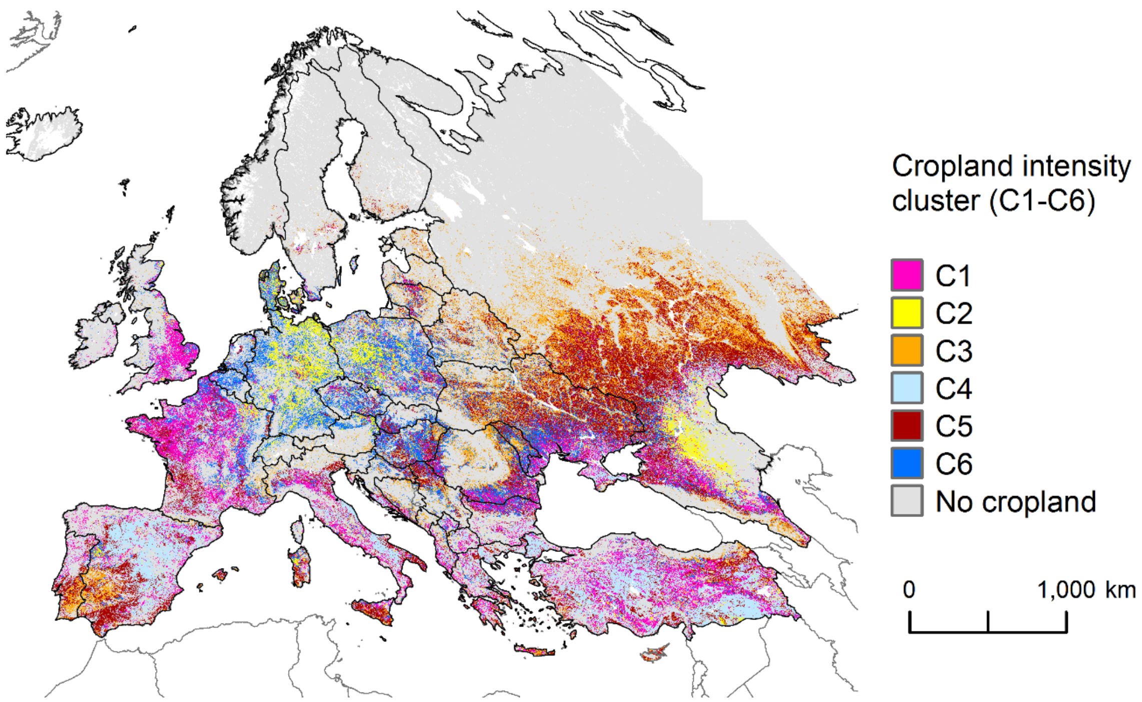

Figure III-5: Cluster of similar cropping systems (C1–C6) mapped using self-organizing maps and our four cropland intensity indicators (cropping frequency, multi-cropping, fallow cycle and crop duration ratio).

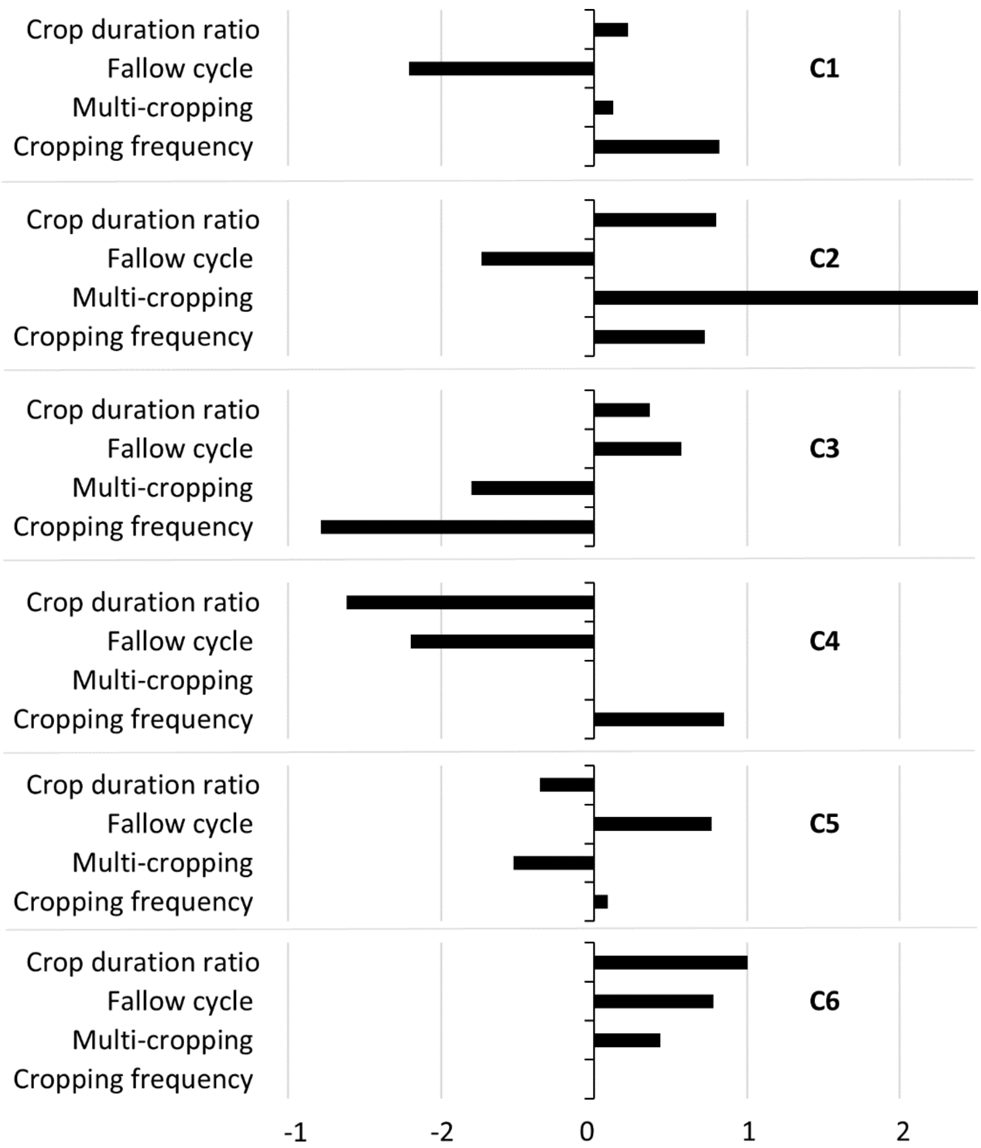

Figure III-6: Z-scores of each indicator characterizing the clusters (C1–C6). Positive and negative numbers signify above-average and below-average values relative to the study region mean.

4 Discussion

Understanding spatial patterns in cropland-use intensity is important for identifying target regions for intensification, and for assessing its potential environmental trade-offs. Better information on cropping systems, including cropping frequency, fallow cycles, multi-cropping, and crop duration, are important indicators in this context; yet agricultural census do not cover them at fine scale. Using a 12-year MODIS NDVI time series, we mapped these cropping indicators at the continental scale for Europe. The cropping patterns we find correspond well with other indicators of agricultural land management in Europe, highlighting the potential for satellite-based cropping measures to support agricultural monitoring. Moreover, our indicators capture important aspects of agricultural intensity, highlighting how management intensity varies in space and time. The identified cropping systems can be explained by agro-environmental conditions (e.g., soil quality, water availability), socio-economic conditions (e.g., rural depopulation), management practices (e.g., irrigation), and crop-specific management (e.g., rice growing in northern Italy). Our satellite-based indicators of cropland-use intensity and the mapping of cropping systems may help to identify baselines and candidate region for intensifying croplands sustainably. The cropping patterns captured by our indicators correspond well with those from other indicators of agricultural management in Europe. For example, existing maps of cropland net primary production, yields, and yield gaps consistently show the highest output intensity where we identified intensive used multi-cropping systems and a long crop duration (Mueller et al. 2012; Neumann et al. 2010) (Monfreda et al. 2008). Maps of fertilizer usage also show highest fertilizer application in these regions (Potter et al. 2010; Temme and Verburg 2011). In contrast, these maps suggest low input and output cropland intensity in eastern Europe, especially in European Russia, Ukraine, and the Baltic States, congruent with our cropping indicators. A more quantitative comparison among our maps and other land-use intensity indicators is not feasible, given different resolutions and time periods covered, and considering that cropland-use indicators related to inputs and outputs usually represent downscaling agricultural statistics (usually national scale). That our satellite-based indicators identify, on a general level, the similar spatial patterns of high and low intensity is encouraging, and highlights the potential of satellite-based to observe and monitor agricultural systems more directly and with finer spatial detail (Kuemmerle et al. 2013; Zaks and Kucharik 2011).

The spatial congruence between our cropping indices and alternative measures of agricultural management, such as fertilizer and yields, also underlines the value of satellite-based cropping indices to more directly measure cropland-use intensity. Yet some of our indicators, for example cropping frequency, (i.e., more cropped years indicates higher intensity) are more closely related to intensity than others (e.g., crop duration ratio). A few points of caution need to be mentioned when interpreting our individual indicators. First, our multi-cropping indicator captured whether there are one or two vegetation peaks in a given year, but not in all cases a second peak refers to a second crop, nor does it attest to whether the second crop was actually harvested or left in the field as green manure. Second, our fallow cycle indicator captured cropping cycles over multiple years, but rests on a reliable identification of active vs. fallow cropland. Although our accuracy assessment of the active/fallow maps suggests these maps are reliable (>90% overall accuracy, Estel et al. 2015), uncertainty for some regions (e.g., with small fields) may be higher than for others. Third, we measured crop duration ratio as the length of the vegetation signal on cropland, but lower crop duration ratios may be due to management or climate. To interpret crop duration ratio as a measure of cropland intensity, agro-environmental conditions and irrigation structure should be considered in future work. Finally, validation of our cropping indicators is challenging because retrospective field-level data on cropping do not exist for larger areas, and in-situ data are currently not feasible to gather at the continental scale. However, we note that the annual fallow/active maps derived in Estel et al (2015a) and used as input data for the cropping intensity indicators cropping frequency and fallow cycle has been validated extensively (Estel et al. 2015), and sensitivity analyses for the crop duration indicator attest to the robustness of these indicators.

SOMs were a useful tool to identify regions with similar cropping and thus to help interpret and reduce complexity in our multi-dimension indicator dataset. The six clusters of cropping systems appear to be related to distinctly different agro-environmental and socio-economic conditions across Europe. Cluster 1 characterized moderately intensive rain-fed cropping and included some irrigated areas in southern Europe along rivers and reservoirs (e.g., Ebro-basin in northern Spain, Po Valley in northern Italy, Black Sea area) (Salmon et al. 2015; Siebert et al. 2006). Irrigation here led to an uncoupling from climate constraints, allowing for central/western European cropping systems in these areas.

Cluster 2 was clearly linked to the most intensified rain-fed cropping in highly favorable agro-environmental conditions (e.g. in Germany and Denmark, Neumann et al. 2010). Interestingly, this system was also found in Europe's east, particularly, in southern Ukraine, Romania and southern Russia, where some of the world's most fertile soils are found (Fischer et al. 2000). High double cropping rates that characterized this cluster (e.g., southern Russia, northern Germany) are linked to the cultivation of winter wheat as main crop. The specific cropping time of winter wheat allows preceding or subsequent crops (e.g., rape, summer wheat) (Gienapp et al. 2012; Schierhorn et al. 2014).

Cluster 3 was characterized by frequent fallow years, occurred mainly in water-limited regions (e.g., Extremadura and northern Andalusia in Spain, southern Portugal). Fallowing was characteristic for semi-arid regions to maintain soil moisture and fertility (Boellstorff and Benito 2005). Interestingly, this cropping system also occurred in eastern Europe, although agro-environmental conditions are more favorable there. The higher fallow frequencies there are possibly a legacy of the breakdown of socialism and the subsequent restructuring of agricultural sectors (EU 2005; Fischer et al. 2000), leading to widespread farmland dis-intensification and abandonment (Kuemmerle et al. 2011; Prishchepov et al. 2012a; Rey Benayas 2007). Similar trends are ongoing in western Europe's marginal regions (e.g., mountain regions) (Gellrich et al. 2007; MacDonald et al. 2000), many of which fell in the same cluster in our analyses.

Cluster 4 was clearly related to rain-fed cropping under water limitation (e.g., the Mediterranean), allowing only for shorter growing seasons (Fischer et al. 2000). This does not necessarily indicate lower cropland-use intensity since yields in this regions can be high (Mueller et al. 2012). For example, rice growing areas in the Po Valley (northern

Italy) had very short crop durations but are considered among the most intensively used croplands in Europe (Blengini and Busto 2009; Erb et al. 2013).

Finally, cluster 5 contained much cropland without major contrains (e.g., accessibility, soil fertility) yet that is currently not used to its full potential. Cluster 6, characterized by high fallow rates, occurred mainly in central and eastern Europe in favorable agro-environmental conditions (e.g., southern Romania, southern Ukraine). Both cluster could entail particularly candidate regions for sustainable intensification.

In sum, our four satellite-based cropping indicators, as well as our cluster analyses to identify similar cropping systems across Europe, appear valuable for broad-scale agricultural monitoring. Satellite-based indicators could therefore complement ground-data that must always remain sample-based with wall to wall observations of agricultural management. Our study showed that time series of satellite images can also help to better characterize cropland-use intensity, and thus to assess baselines and potentials for intensifying croplands sustainable. Such information is critical to scrutinize the possible socio-economic and environmental trade-offs, as well as synergies, of intensifying croplands.

Acknowledgements

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Supplementary Information

III-S1. Study area

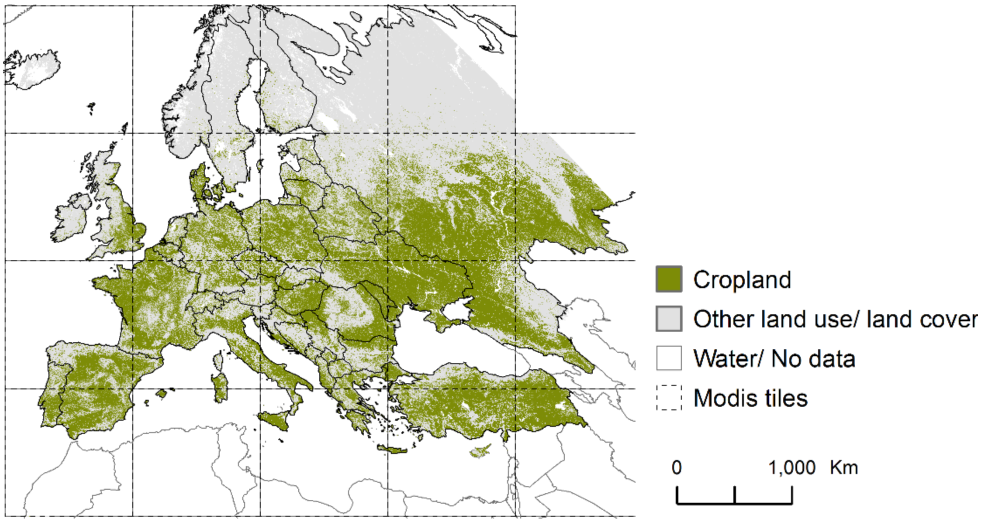

Figure III-S1: Study area, consisting of 19 MODIS tiles, and the cropland extent derived from the GlobCORINE 2005 map. We focused on all classes containing cropland, specifically rainfed and irrigated cropland, complex cropland, and mosaic cropland / natural vegetation, and we masked all other classes.

III-S2. Calculation and sensitivity analyses of cropping indicators

Cropping frequency

The cropping frequency was calculated using 12 annual, binary maps of fallow active farmland from 2001 to 2012 derived in a previous study (Estel et al. 2015) (Figure III-S2). These maps were classified using a geographically well-distributed training dataset for each year and a Random Forests classifier. The validation for each of the 12 active/fallow maps based on independent observations from the field (i.e. Land Use/Land Cover Area Frame Survey; LUCAS) and from satellite images (i.e. Landsat). Overall we collected for each year on average 438 validation points for the fallow and 1870 points for the active class. The overall accuracy of the fallow/active farmland maps were on average 90%. The active farmland class had a higher accuracy, with a producer's accuracy of 92% on average and a user's accuracy 96% on average. The fallow class had a producer's accuracy of 83% on average and a user's accuracy of 70% on average (see for details Estel et al. 2015).

We calculated the cropping frequency by summarizing the 12 annual maps and counting the number of active years during that time period for each pixel.

(1)

$$Cropping\ frequency = \sum_{i=1}^{12} y(i)$$

The overall accuracy of the fallow/active farmland maps used as input were on average 90%. The active farmland class had a higher accuracy, with a mean producer's accuracy of 92% and a mean user's accuracy of 95%. The fallow class had a mean producer's accuracy of 83% and a user's accuracy of 74% (Estel et al. 2015).

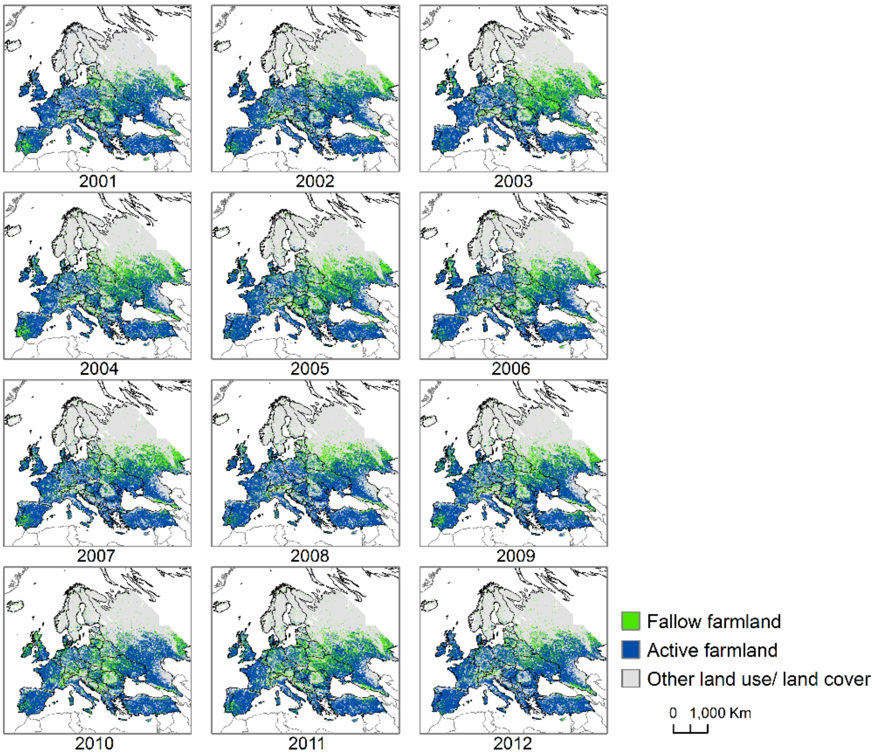

Figure III-S2: Annual maps of fallow and active farmland across Europe from 2001 to 2012, derived from MODIS NDVI time series at a spatial resolution of 231.6 m.

<u>*Multi-cropping*</u>

The multi-cropping indicator was derived by counting the number of annual seasons over the entire time period using the software TIMESAT (Jönsson and Eklundh 2004). The determination of the number of seasons per year based on the base level and the amplitude ratio between the primary and the secondary peak of the two seasons. We mapped for each year in our time series (2001-2012) the number of seasons (single or double-cropping) maps and summarized the number of years with double cropping:

(2)

$$Multi\ cropping = \frac{1}{2} \times \sum_{i=2}^{24} s(i)$$

The data base for the determination of the annual season was the smoothed and normalized NDVI time series (see for details Estel et al. 2015). The normalization procedure allows the comparison of vegetation phenology all over Europe despite the strong climate gradient and the different timing of green-up and peak vegetation (e.g., shifted vegetation peak in the Mediterranean region, higher seasonality in the North).

Fallow cycles and fallow cycle index

The derivation of the fallow cycles based on the 12 annual, binary maps of fallow active farmland from 2001 to 2012 derived by Estel et al. 2015a, and described above (Figure III-S2). We screened the twelve-year time series for three different fallow cycle types (FC1, FC2, and FC3). Each cycle type was built by chain segments; a certain number of consecutive fallow years enclosed from two active years. Thus a chain segment of FC 1 consists one fallow year, a chain segment of FC2 two consecutive and a chain segment of FC3 three consecutive fallow years enclosed by active years. We then summarized the total number of chain segments within the entire time series for each fallow cycle type (Fig III-S3).

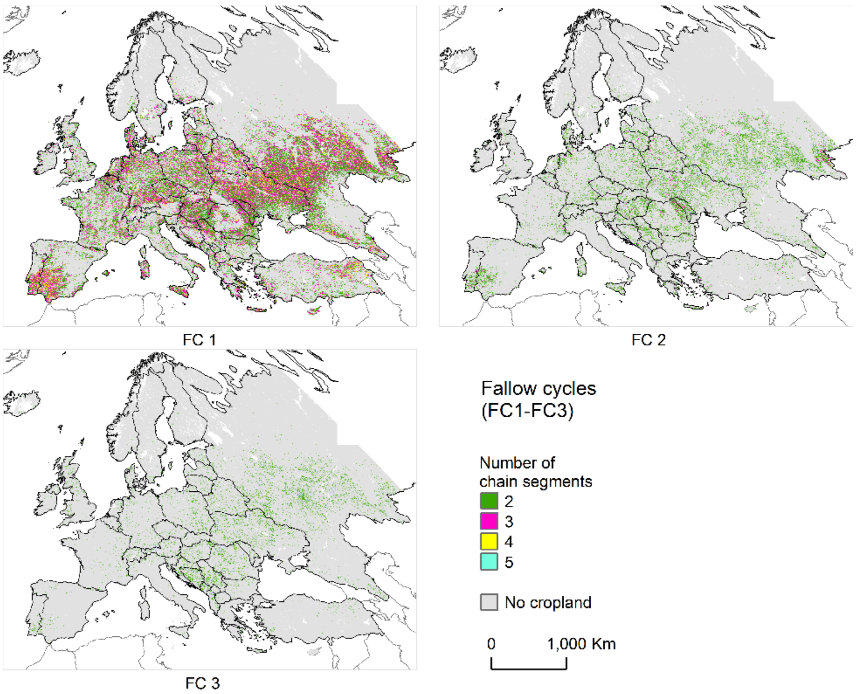

Figure III-S3: Show the total number of chain segments for the three fallow cycle types (FC1, FC2, and FC3). The maximal number of chain segments for FC1 in a twelve year time series is five, for FC2 three and FC3 can consists only two chain segments.

To provide a single indicator for fallow systems and a measurement for the cropland intensity within these fallow systems we attached different weights to the three fallow cycle type. The weights were derived by calculating the ratio of the total number of years in the time series (in our case twelve years) and the maximal possible number of chain segments within the time series. In a twelve year time series FC1 can occurred five times (5/12), FC three times (3/12) and FC3 only two times:

$$Fallow\ cycle\ index = \sum_{i=1}^{5} \left(FC1 * \frac{5}{12}\right) + \left(FC2 * \frac{1}{4}\right) + \left(FC3 * \frac{1}{6}\right) \tag{3}$$

Since a single chain segment does not indicate cyclicity or cropland intensity within fallow systems, we considered only time series with at least two chain segments. The resulting index ranges from 0.33 to 2.08. The highest index value describes time series with yearly changes from active to fallow over the entire time period. The lowest value describes time series consisting only two chain segments from the same fallow cycle type or a combination of two types. Thus as higher the index value as higher the number of chain segments and the number of equal chain segments.

Crop Duration Ratio

The crop duration ratio refers the relationship between the total length of the growing season (L0) and the length of the cropping season at half of the highest peak (i.e., half-maximum, L50) during the cropping time (Figure III-S4). The total length of the growing season was determined by counting the number of days with a land surface temperature above 5°C, i.e., the time between the earliest and latest MODIS acquisition date in a given year when plants are assumed to actively grow (Hickler et al. 2012; Zhang et al. 2004). We derived the crop duration ratio from L0 and L50 for each non-fallow year between 2001 and 2012 (Figure III-S5) and calculated the mean across all years.

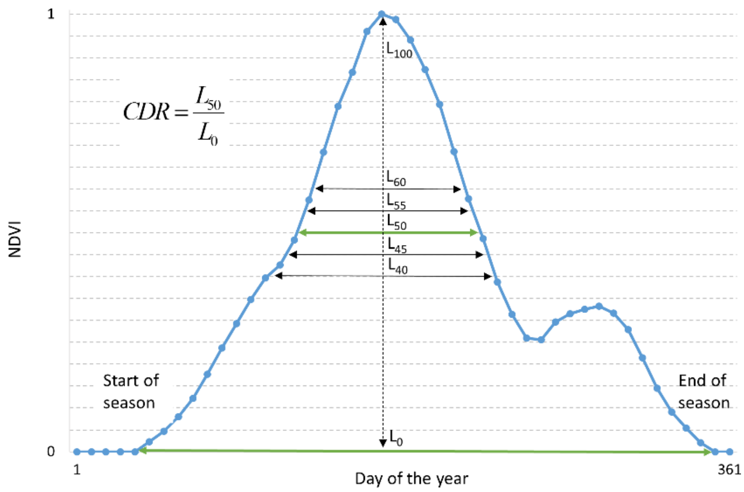

Figure III-S4: Calculation of Crop duration ratio (CDR) using the total length of the growing season (L0) and the 50% of the peak vegetation (L50).

To assess the sensitivity of our results towards the threshold chosen to map the crop duration ration (the half maximum, 50% peak vegetation threshold, in the default calculation) we derived crop duration ratio maps for 40%, 45%, 50%, 55%, and 60% thresholds for each year (Figure III-S4), calculated the average crop duration ratio per pixel, and then derived the standard deviation crop duration ratio per pixel (Figure III-S5). Our results showed that the crop duration ration was relatively robust to the choice of threshold for most cropland areas in Europe (i.e., variation of less than 20%). For some areas, especially in the Mediterranean, where crop duration ratio is lower than in other areas in Europe, we found a higher, but still fairly moderate sensitivity (e.g., in Turkey, on Crimea Fig. S5). (e.g., in Turkey, on Crimea Fig. III-S5).

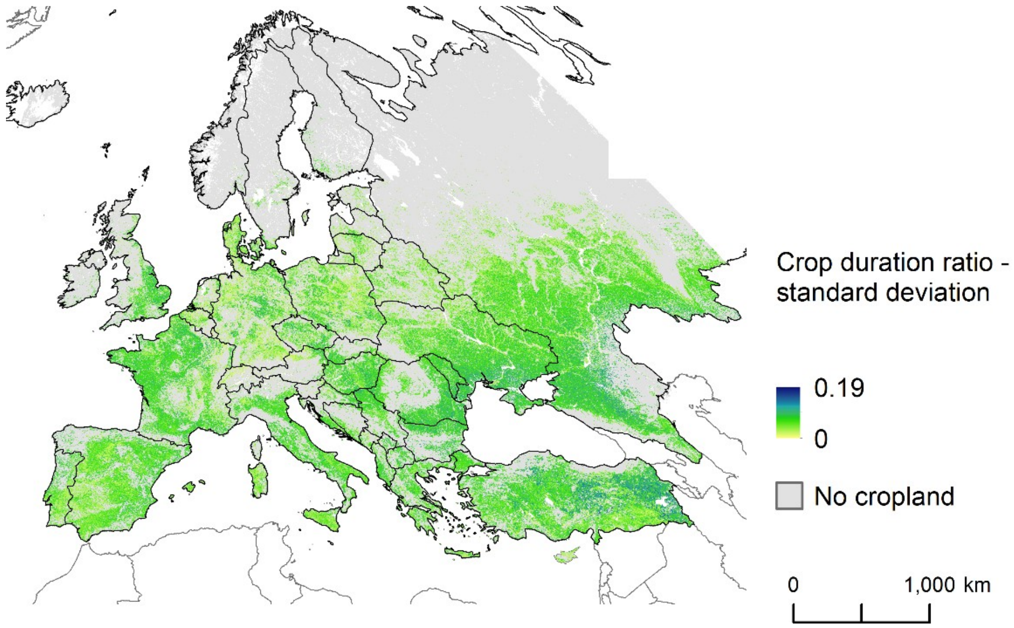

Figure III-S5: Standard deviation crop duration ratios for thresholds between 40% and 60% peak vegetation.

III-S6. Self-Organizing Maps parameterization

Determination of the optimal cluster number

To determine the optimal number of cluster for the SOM analysis, we carried out a sensitivity analyses with varying clusters numbers and dimensionality (i.e., columns and rows) ranging from 2 x 2 to 4 x 4. To identify the optimal cluster number we observed the natural breakpoint in the mean distance of the samples to their cluster centroid (Maulik and Bandyopadhyay 2002) and the Davies-Bouldin cluster validity index which explore the intra- and inter-cluster variability (Davies and Bouldin 1979). A low Davies-Bouldin index indicates a mathematically more satisfactory clustering result. In our case the minimum Davies-Bouldin value was at six. Since the mean distance to the cluster centroid was levelling off around a cluster size of six as well, we set the optimal number of cluster to six (Fig III-S6).

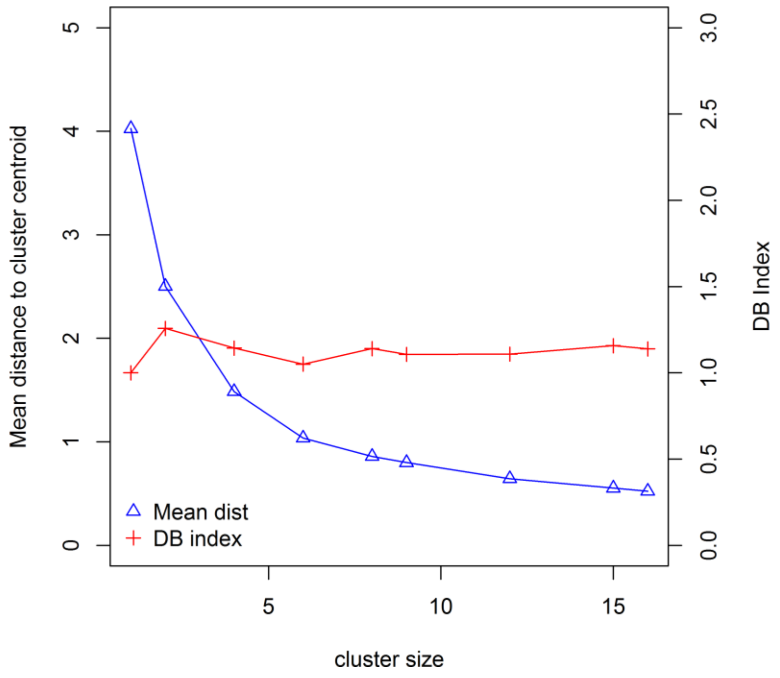

Figure III-S6: Determination of the optimal cluster number using the mean distance of samples to their cluster centroid and the Davies-Bouldin cluster validity index.

Table III-S1: Shows the z-score values for each indicator.

Z-score	C1	C2	C3	C4	C5	C6
Cropping frequency	0.82	0.72	-1.78	0.85	0.09	0.00
Multi-cropping	0.12	2.76	-0.80	0.00	-0.53	0.44
Fallow cycle	-1.25	-0.67	0.73	-1.23	0.73	0.74
Crop duration	0.22	0.80	0.36	-1.62	-0.35	1.00

Chapter IV:
Mapping grassland-management intensity in Europe combining satellite data and agricultural statistics

(in preparation for Environmental Research Letters)

Stephan Estel, Sebastian Mader, Christian Levers, Peter H. Verburg, Matthias Baumann, Tobias Kuemmerle

Abstract

The world's grasslands, both natural and managed, provide important ecosystem services such as carbon sequestration, protecting soil fertility, controlling soil erosion and regulating the hydrological cycle. Most grasslands today are used for livestock grazing or fodder. Yet, little is known about the spatial patterns of grassland-management intensity, especially at broad geographic scales. This is important because the level of management intensity influences ecosystem properties, ecosystem services, and biodiversity in critical ways. Using the European Union (EU) as a case study, we developed a method to map grassland-management intensity at a 3x3-km² scale along the three grassland intensity dimensions: (1) mowing frequency, (2) fertilizer application, and (3) grazing pressure. To capture mowing, we used Moderate Resolution Image Spectroradiometer (MODIS) normalized difference vegetation index (NDVI) time series between 2001 and 2012 and a count of mowing events throughout the year by using the local extrema determined from a spline curve. For fertilizer application and livestock density, we used agricultural statistics on grasslands. We combined all three dimensions to derive two grassland-intensity index maps and a map depicting regions of similar grassland management systems across the EU. Our MODIS-based mowing index captured up to five mowing events per year and spatial patterns of mowing frequency matched well with existing maps of grassland productivity gradients across Europe. We identified six clusters of similar grassland management systems, highlighting the multidimensional nature of grassland-management intensity. Our resulting maps show the diverse spatial patterns in management intensity of the EU's grasslands, with high management intensity in Ireland, northern and central France, and the Netherlands. Intermediate intensity occurred in parts of the United Kingdom, central France, northern and central Spain, Germany, and eastern Poland. Low-intensity grasslands were mainly found in mountainous regions, in the Extremadura in Spain, and some East European regions. Our analyses emphasize how the combination of satellite images and agricultural statistics can improve grassland monitoring at broad geographic scales.

1 Introduction

Grasslands cover more than 40% of the Earth's land surface and are widely used for livestock grazing and fodder production, thereby contributing to global food production and food security in major ways (FAO 2005). As the global human population continues to grow, and consumption rises, agricultural production will have to increase two or three-fold in the next decades (Erb et al. 2013; Krausmann et al. 2013). Changing food preferences are major driver of this increasing demand, with diets becoming richer in animal protein, including grassland-based livestock products (Kastner et al. 2014; Keyzer et al. 2005; Thornton 2010). This development will further increase the pressure on world's grasslands, and lead to increased competition between livestock production and other grassland use, thus affecting grassland functioning, stability, and biodiversity (FAO 2006; Hopkins 2006; Laliberté et al. 2010).

Besides food, grasslands provide a wide range of ecosystem services, many of which are non-provisioning in nature. Grasslands play an important role in carbon sequestration by storing around 15% of the global organic carbon (Tate and Ross 1997), protect soil fertility and control soil erosion and influence the hydrological cycle (Lemaire et al. 2005; Sanderson et al. 2007; Weigelt et al. 2009). Likewise, grasslands support high levels of unique biodiversity (Cremene et al. 2005; Parr et al. 2014). This is true for natural grasslands, such as temperate steppes, tropical savannas, or alpine meadows, which often harbor endemic or charismatic species; but also for semi-natural grasslands resulting from a long history of land use (Batáry et al. 2015; Linnell et al. 2015). Semi-natural grasslands in Europe for example are one of the most species-rich vegetation communities in the world (Dengler et al. 2014; Wilson et al. 2012) and therefore a key target for biodiversity conservation (Sutcliffe et al. 2015; Sutherland 2002). Both biodiversity and the level of non-provisioning ecosystem service flows, strongly depend on grassland-management intensity. Biodiversity values are tightly linked to grasslands with low-intensity management, such as in traditional farmland landscapes, but are losing out in more intensive used grasslands (Laliberté et al. 2010).

Therefore, understanding management intensity in grassland systems is crucial. Yet, appropriate monitoring systems are missing for most parts of the world (Garnett et al. 2013b; Thornton and Herrero 2010). As a result, only a few indicators of grassland-management intensity are available for larger areas, and these indicators are often very coarse in scale and represent snapshots in time (Kuemmerle et al. 2013; Verburg et al. 2011). Two main challenges connected to mapping grassland-management intensity explain this. First, while satellite remote sensing has emerged as the main tool for mapping changes in land use and land cover (Pettorelli et al. 2014a; Pettorelli et al. 2014b; Rindfuss et al. 2004), direct mapping of grassland intensity from satellite images (Kuemmerle et al. 2013) remain challenging. Grassland use is characterized by only subtle changes in biomass and vegetation (e.g., grazing), or the alteration of the vegetation signal only over short time periods (e.g., mowing). Second, grassland-management intensity is a complex multidimensional issue (Bernhardt-Römermann et al. 2011; Herzog et al. 2006) with three main practices contributing to management intensity: (1) mowing frequency, (2) fertilizer application, and (3) grazing pressure (Allan et al. 2014; Blüthgen et al. 2012). These three dimensions are not fully independent from each other. For example, fertilizer application is often required to allow for higher mowing frequencies (Bernhardt-Römermann et al. 2011), and grazing and mowing do not have to be mutually exclusive as nitrogen release from livestock may increase biomass yields and thus allow for mowing later in the season (Blüthgen et al. 2012). Assessing grassland-management intensity, thus, requires monitoring systems that embrace the multidimensional nature of intensification.

However, only a few studies have mapped grassland-management intensity across large areas. For example, the spatial distribution of livestock in Europe was modeled at the continental scale using livestock statistics at the province level (Nomenclature of Territorial Units for Statistics level 2, NUTS 2) and a statistical downscaling approach (Neumann et al. 2009). Similarly, maps of fertilizer application on EU's grasslands were generated using nitrogen input statistics at NUTS2-level and regression models (Temme and Verburg 2011). At the global scale, the spatial distribution of key livestock species was mapped using subnational livestock statistics (FAO 2007), which then was used to model the distribution of livestock production systems at different management intensity using country-level agricultural statistics (Robinson et al. 2014). Similarly, global patterns of fertilizer application and manure production were disaggregated from agricultural statistics (Potter et al. 2010). All of these studies are restricted to relatively coarse grains, and the statistics of these maps may contain substantial uncertainties (Verburg et al. 2011; Zaks and Kucharik 2011). Moreover, existing studies mostly focused on a single grassland-management intensity indicator, mainly from livestock and fertilizer application, whereas maps of mowing frequency simply do not exist for larger areas. A consistent and spatially detailed assessment of all three main dimensions of grassland-management intensity (i.e., mowing, fertilizer, grazing) for larger areas has not been carried out for any world region so far.

Satellite remote sensing can help to fill this gap. Particularly, dense time series of medium-resolution satellite images, such as those from the Moderate Resolution Imaging

Spectroradiometer (MODIS) can overcome limitations in mapping land-use intensity due to their high temporal resolution, which captures even subtle vegetation and biomass changes, and can separate phenological changes from management changes (Friedl et al. 2010). For example, MODIS Normalized Difference Vegetation Index (NDVI) time series were used to quantify grazing intensity, by correlating NDVI-values and observed plant biomass in the Inner Mongolia (Kawamura et al. 2005). The impact of livestock grazing in the northern Kenya rangelands was monitored by comparing NDVI images before and after grazing (Ritchie 2014). Harmonic functions fitted to NDVI phenological curves were used to quantify seasonal and inter-annual changes due to grazing in the transition zone between grassland and bare areas in the Gobi desert (Hilker et al. 2014). Likewise, the frequency of fallow years on farmland (including pastures) was mapped for all of Europe using a Random Forest classifier and MODIS NDVI time series (Estel et al. 2015). All of these studies highlight the potential of MODIS time series to capture indicators of grassland-management intensity. Moreover, most remote-sensing-based grassland management studies focused on grazing intensity, although local studies suggest mowing can be captured from satellite image time series (Asam et al. 2015). Cropping cycles, phenologically similar to mowing cycles, have been successfully mapped for several areas, including Europe (Estel et al. 2015b) Brazil (Galford et al. 2008; Spera et al. 2014), India (Biradar and Xiao 2011), the Mekong Delta (Sakamoto et al. 2009), China (Li et al. 2014), and the mid-western United States (Wardlow and Egbert 2008). This suggests that the potential of satellite-based broad-scale mowing indicators has not yet been fully explored.

Our goal here was to develop a remote sensing based method capturing spatial patterns in mowing frequency and to combine these with agricultural statistics data on fertilizer application and livestock density in order to assess grassland-management intensity comprehensively. Europe is interesting in this regard, because it includes 57 million hectare (Mha) of permanent grassland areas (EU27, 2007) (Huyghe et al. 2014), which span across strong environmental gradients, from the boreal to the Mediterranean, and are managed at varying intensity, from traditional to agri-business farming. Moreover, most land-use change in Europe today occurs along gradients of intensification (Rounsevell et al. 2012; Rudel et al. 2009). Finally, Europe's long agricultural history results in cultural landscapes with semi-natural grasslands as a key element characterized by high aesthetic value, rich cultural heritage, and much farmland biodiversity (Angelstam et al. 2003; Poschlod and Bonn 1998; Stoate et al. 2009). These landscapes are threatened due to intensification (Henle et al. 2008; Kleijn et al. 2009) and farmland abandonment (Gellrich et al. 2007; Kuemmerle et al. 2011;

Prishchepov et al. 2012a). Better knowledge about the spatial patterns of grassland-management intensity is important to identify where traditional farming landscapes may be at risk (Strijker 2005). We specifically assessed following research questions:

1. *What are the spatial patterns of mowing on EU's grasslands, as mapped from MODIS NDVI time series?*
2. *How do combined metrics of mowing frequency, fertilizer application, and grazing pressure determine the spatial patterns of grassland-management intensity across Europe?*

2 Data and Methods

Our methods combine data sets from different sources and at different spatial resolutions to derive a set of grassland-management intensity indicators for the entire EU within the 2007 borders (without Cyprus and Greece, which was not covered in the CORINE 2006 - Coordinated Information on the European Environment; see below). First, we used a pre-processed MODIS NDVI time series from 2001 to 2012 to derive three indicators of mowing intensity: (1) MI 1 pertaining to the average number of mowing events per year for each year where management was detected, (2) MI 2 pertaining to the average number of mowing events over the full observation period, (3) the management frequency pertaining to the number of years mowing took place. Second, we combined the mowing indicator (MI 1) and downscaled grid-level statistics on fertilizer application and livestock density to derive grassland intensity indices (CGI), as well as spatial clusters of similar ***grassland management in*** the EU. We assessed all EU's grasslands based on the grassland extent from the CORINE land-cover product 2006. ***The CORINE land-cover classification (CLC) consists of 44 classes and based on national-level in-situ data and satellite image interpretation between 2005 and 2007*** (EEA 2008). ***For our analysis, we used the CLC grassland classes 'Pasture' and 'Natural grassland' (Figure IV-1).***

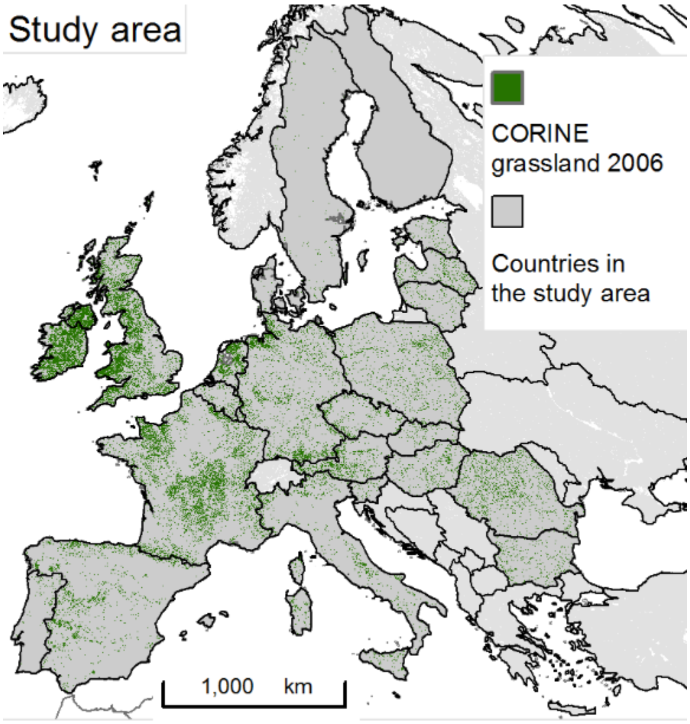

Figure IV-1: Study area and the CORINE 2006 grassland extent within the European Union Member states in 2007 (without Cyprus and Greece).

2.1 MODIS-based indicators and indices

To map the MODIS based indicators, we used combined MODIS NDVI time series from the satellites Aqua and Terra from 2001 to 2012. We pre-processed all images to improve the quality of the NDVI time series (Estel et al. 2015). Specifically, we used the MODIS quality information, the MODIS land surface temperature, and the MODIS land-water mask, to exclude poor and missing observations (e.g., clouds, water, snow, and ice). We interpolated the resulting missing values and smoothed the NDVI time series using a Savitzky-Golay filter. We then normalized time series to a scale between zero and one in order to improve the comparability of our data regarding the strong climate variations across Europe (e.g., late green-up and higher seasonality in the north). For the same reason, we shifted the time series for those pixels that showed a vegetation peak in winter (e.g., in the Mediterranean). A more comprehensive description of the pre-processing is given in Estel et al. (2015a).

Mowing frequency

We used the pre-processed NDVI time series to calculate the mowing frequency (number of mowing events) for each year of the time series. The calculation followed the assumption that mowing represents a disturbance-type event in the phenological profile of grassland, resulting in distinct features over the growing season. Unmanaged grassland is typically characterized by a smooth, bell-shaped NDVI profile over a given growing season (Estel et al. 2015). In contrast, mowing leads to abrupt changes (i.e., disturbances) in the phenological NDVI profile of grassland, which thus differ substantially from those of unmanaged grasslands. Managed grassland is often characterized by multiple peaks and troughs (i.e., mowing disturbances type), as well as by smaller NDVI integrals over the growing season due to biomass removal, Figure IV-2).

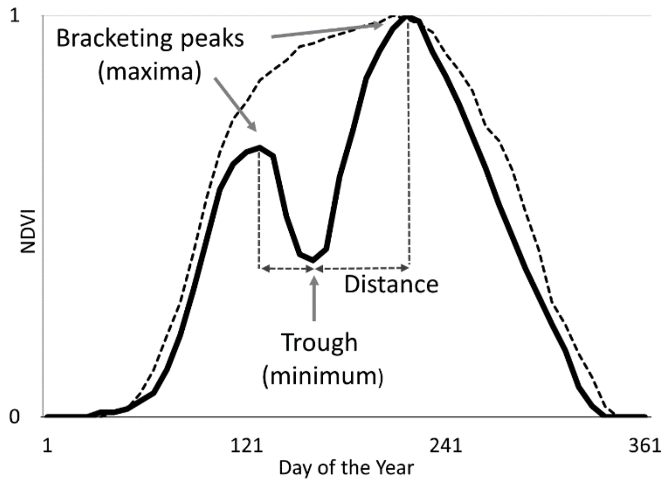

Figure IV-2: Phenological MODIS NDVI profiles of unmanaged (dotted line) and managed grassland with one mowing event (solid line) characterized by a series of vegetation peaks (maxima), troughs (minima), and their distances.

Using these distinct features of mown and unmanaged grasslands, we mapped the mowing frequency by counting the number of troughs in the NDVI profile over the year, assuming that the number of peak (maxima) and trough (minima) sequences during the vegetation period represents mowing (Asam et al. 2015; Schuster et al. 2015). To analyse the structure of annual vegetation profiles, and thus sequences of peaks and troughs therein, we used a SPLITS (Spline Analysis of Time Series) algorithm (Mader 2012). SPLITS is a framework for a multi-purpose phenological description of remotely sensed time series based on polynomial spline models. In our case, an endpoint-interpolating, uniform B-spline curve (de Boor 2001) consisting of 120 polynomial pieces was fitted to the times series using a least squares method. B-spline representations are especially useful for describing time series features when time series are continuous, rather than consisting of discrete time steps, such as estimating higher order derivatives from noisy signals. Differentiation, and thus the search for extrema can be performed efficiently in a signal's B-spline domain (Unser et al. 1993). Accordingly, the B-spline model was used to determine the extrema (vegetation peaks and troughs) within annual sections of the NDVI time series. Relevant features were identified by comparing the value of a minimum in relation to the values of the maxima bracketing (i.e., surrounding) a given minimum. Bracketing maxima were obtained by a recursive subdivision technique. The first subinterval was defined by the first and last local maxima occurring in a given year. Subsequently, the highest local maximum within this interval, which is higher than any of the maxima bracketing of the interval, also became a bracketing maximum, thus subdividing the first interval into two. The concept is then reapplied recursively to produce further subdivisions. In this way, any local minimum (i.e., trough) within a given growing period year can be attributed to two bracketing maxima. In our case, a trough feature was considered relevant if the ratio of its NDVI value to the weighted average of the NDVI values at the bracketing maxima exceeded a certain, user-defined threshold. The linear weights for computing the average between the two peak values were determined by the inverse distance, in time, of the bracketing maxima to a given trough (Figure IV-2). We counted up to five mowing events (Figure IV-3), resulting in six mowing frequency classes (0 to 5 mowing events). Due to the very small number of mowing classes with three, four or five mowing events, we aggregated these classes into a single class. This resulted in a series of annual maps from 2001 to 2012 showing four mowing classes (i.e., ‘none’, ‘one’, ‘two’, and ‘three or more’).

We determined the optimal threshold ratio by first calculating mowing events for a wide range of thresholds, ranging from 0% to 90% (in 10% steps). Second, we selected a random sample of 25 points per class from the threshold-free mowing frequency map (0% = counting all peaks) and for each year (2009 and 2012). We then cross-checked the resulting 300 points by visual interpretation of the normalized NDVI profile (i.e., counting the actual troughs). Finally, we calculated the true positive rate (i.e., agreement between mowing events identified visually and by our algorithm) for each threshold from 0% to 90% and selected the threshold with the highest true positive rate.

Validation of the mowing frequency

For the mowing frequency map associated with selected threshold, we calculated standard accuracy metrics, including an error matrix, and overall and class-wise user's and producer's accuracies. We corrected all accuracies and area estimates for potential sampling bias and calculated the 95% confidence intervals around the area estimates (Foody 2002; Olofsson et al. 2013).

To further test the robustness of our map, we used independent ground observations of grasslands from the LUCAS surveys conducted in 2009 (23 countries) and 2012 (27 countries). While mowing is not explicitly registered in the LUCAS classification, mown grasslands were identified by excluding all other grassland management classes (i.e., grazed areas) as well as unused or abandoned grasslands. For unmanaged grassland, we used the

LUCAS land-use classes 'fallow' and 'unused and abandoned areas'. To ensure comparability between the LUCAS observations and the MODIS data, we selected only those LUCAS points which fulfilled the following conditions: (1) the LUCAS point was located in a field larger than 10 ha; (2) at least 75% of the observed field was covered by grassland; and (3) the distance of the LUCAS point and the MODIS pixel centroid did not exceed 50 m (Estel et al. 2015). Additionally, we cross-checked all points against the pre-processed NDVI profiles and high-resolution images available in Google Earth to rule out mismatches (e.g., mowing event after a surveyor labeled a plot as unused) or spatial misalignment (e.g., surveyed field only partly within a MODIS pixel). This yielded in 481 mowing points and 353 unmanaged grassland points (Figure IV-4). We then compared the distribution of mowing events detected in our analyses for both types of ground observations. Since the LUCAS database does not provide mowing frequencies, we simplified the calculated mowing frequency map in accordance to the LUCAS classes 'Mowing' and 'Unmanaged' and calculated as well standard accuracy metrics that we corrected for potential sampling bias and calculated the 95% confidence intervals around the area estimates.

Mowing indices

From the resulting mowing frequency, we calculated two different mowing indices. We summarized the annual mowing frequency maps across all years by calculating the average number of mowing events only for those years which were actual managed (MI 1) - the number of actual managed years were taken from a previous analysis (see grassland management frequency below) and the number of mowing events averaged over the full twelve year period (MI 2).

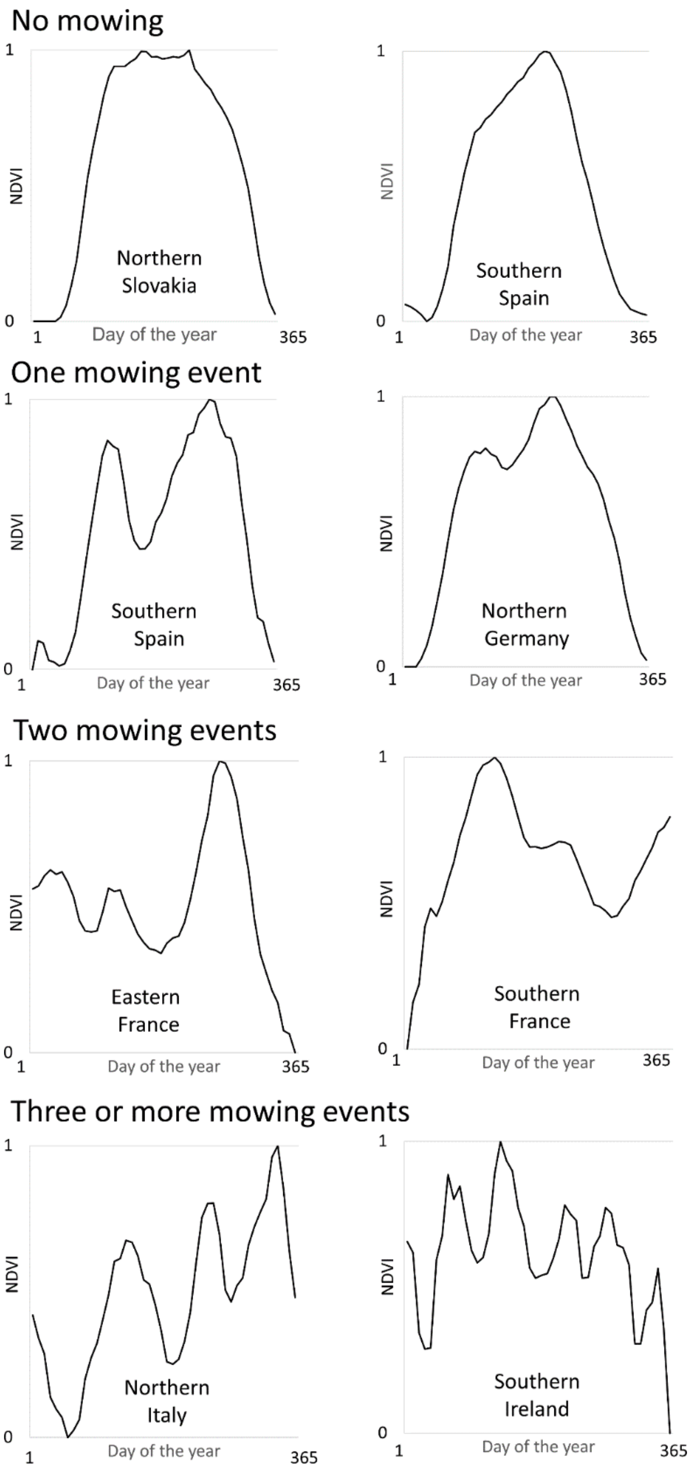

Figure IV-3: Selection of temporal NDVI profiles across Europe showing different types of mowing frequencies.

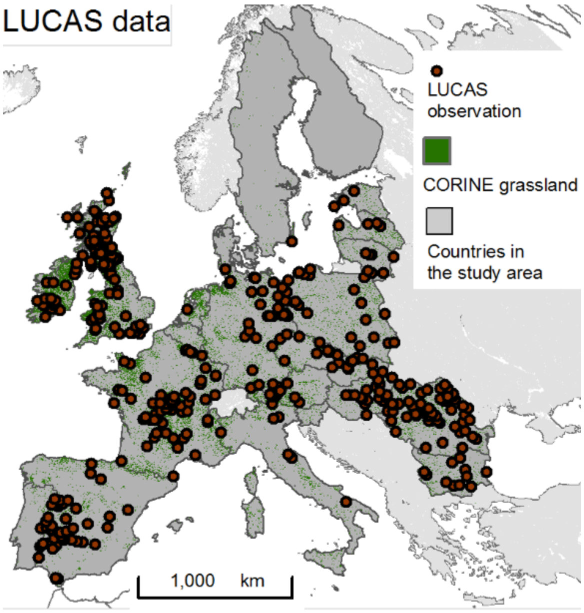

Figure IV-4: Distribution of the validation points derived from the LUCAS survey 2009 and 2012.

Grassland management frequency

As a second indicator of grassland intensity, we mapped the grassland management frequency, defined as the number of years a grassland pixel was managed from 2001 to 2012. The frequency was derived using annual maps managed (active) versus unmanaged (fallow) farmland from a previous analysis. These maps were generated using a Random Forests classification and an extensive training data set for every year from 2001 to 2012 (Estel et al. 2015). We had validated these maps using an extensive ground data set based on the LUCAS surveys from 2009 and 2012, yielding an average overall accuracy of >90% (Estel et al. 2015). In the current study, we masked all non-grassland areas from the managed/unmanaged time series.

2.2 Fertilizer application and livestock density indicators

The fertilizer application, data set based on an existing map that provides nitrogen application rates at a resolution of 1x1-km² for all grassland areas in the EU in two classes: low nitrogen application (0–100 kg N/ha) and high nitrogen application (>100 kg N/ha) by assuming a uniform quantity of 100 kg N/ha per cow for the year 2006. (Overmars et al. 2014; Temme and Verburg 2011). In case of livestock density, we used agricultural statistics on cattle, sheep, and goats at NUTS0 to NUTS2 level that were classified into four livestock unit (LSU) classes: (1) 0-25 LSU/km², (2) 25-50 LSU/km², (3) 50-100 LSU/km², and (4) >100 LSU/km² (Temme and Verburg 2011). These data were then downscaled to the 1x1-km² resolution using regional regression models and a suite of environmental and socio-economic predictors (Neumann et al. 2009; Temme and Verburg 2011).

2.3 Mapping multi-dimensional indicators of grassland-management intensity

Grassland management indices

For ensuring comparability of our indicators at various spatial scales and for visualization purposes, we aggregated all indicators to a target grid of 3x3-km². For the MODIS indicators, this was done via simply calculating the mean value for all grassland pixels in a 3x3-km² grid. For fertilizer, we calculated the area share of the high nitrogen application class per 3x3-km² grid cell. For livestock, we calculated the average LSU across all grassland pixels by using the class mid-points (1) 12 LSU/km², (2) 37 LSU/km², (3) 75 LSU/km², and (4) 150 LSU/km².

We generated two combined grassland intensity indices (CGI) that integrate the three dimensions of intensity, i.e., mowing, fertilizing and grazing (Blüthgen et al 2012). This index was originally developed based on around 150 grassland sites in Germany:

$$L_i = \frac{F_i}{F_R} + \frac{M_i}{M_R} + \frac{Gi}{G_R} \quad \text{(after Blüthgen et al. 2012),}$$

where F_i is the fertilization level (kg nitrogen ha^{-1} year^{-1}), M_i the frequency of mowing per year and G_i the grazing intensity, reflected by the density of livestock (livestock unit days of grazing ha^{-1} year^{-1}) on site i for a given year; and F_R, M_R and G_R their respective mean within the region (R) for that year (i.e., the mean across all 50 experimental plots). By integrating these components, the three dimensions of grassland management are reduced to a single index value (Blüthgen et al. 2012). To make this calculation applicable to the continental scale and to our data format, we first standardized the mowing index (MI 1), fertilizer, and grazing indicators to scale between zero and one, and then applied the formula above to yield a grassland intensity index (CGI_{sum}). In addition to the formula suggested by (Blüthgen et al. 2012), we also tested an alternative based on retaining only the maximum value of any of the three dimensions (CGI_{max});

$$CGI_{\max} = \max\left(\frac{F_i}{F_R}, \frac{M_i}{M_R}, \frac{Gi}{G_R}\right).$$

Thus, whereas for CGI_{sum} it is assumed that the three intensity components are additive, for CGI_{sum} it is assumed that grassland should be identified as intensively managed if any of the three components loads high, thus reflecting the different management types of grassland that can all range from low to high.

Identifying clusters of similar grassland management

We identified typical clusters of grassland-management intensity across Europe using Self-Organizing Maps (SOMs, Kohonen 2001) and the four indicators: mowing index (MI 1), grassland management frequency, fertilizer application, and grazing pressure. SOMs are a clustering technique allowing to reduce a high-dimensional data set to a two dimensional map by grouping observations according to their similarity (Skupin and Agarwal 2008). To identify the optimal number of clusters, we carried out sensitivity analyses with SOM clusters varying from 2 x 1 to 5 x 5 clusters. We then used the Davies-Bouldin index which compares intra- and inter-cluster variability (Davies and Bouldin 1979) to pick the optimal SOM dimensionality. For the cluster analysis, we used the *kohonen* (Wehrens and Buydens 2007) and *clusterSim* (Walesiak and Dudek 2014) packages in R (R Core Team 2014).

3 Results

Mapping mowing frequency from the MODIS NDVI time series yielded a reliable map, with an overall high agreement with independent ground observations of mown and unmanaged grasslands from the LUCAS surveys 2009 and 2012. For around 99% and 97% of the points labeled as unmanaged by LUCAS observers on the ground in 2009 in 2012, respectively, our spline-based algorithm did not detect any mowing disturbance. Conversely, for around 78% and 89% of the points labeled by LUCAS observers as having management other than grazing, we did find at least one mowing signal. This suggests a somewhat higher error of omission than commission for the mowing class, and an overall accuracy of 85.8% for 2009 and 80.2% for 2012 after correcting for the uneven distribution of the two classes (Figure IV-5).

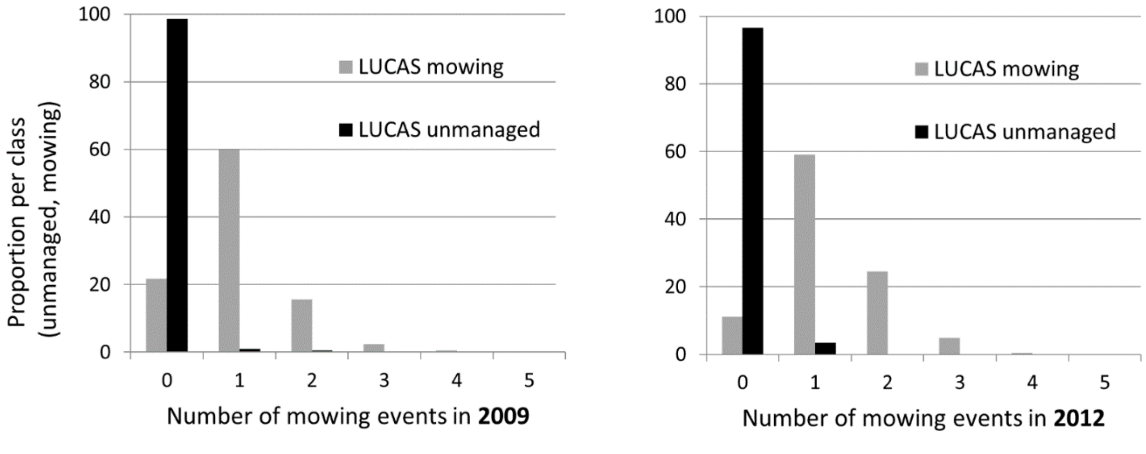

Figure IV-5: Distribution of LUCAS mowed and unmanaged observations within the calculated mowing frequency classes for the years 2009 and 2012.

By comparing the true positive rate across a wide range of thresholds used to consider the difference between a trough and its neighboring peaks as a significant disturbance, we found that the true positive rate of all mowing classes decreased rapidly after a threshold of 10% (Figure IV-6). Some classes, especially in 2009, also had a hump-shaped true positive rate, peaking at 10%. We, therefore, selected the 10% threshold as the ratio for further analyses, which means that we counted all troughs that had a distance of at least 10% to their neighboring peak. True positive rates were higher for the class with three or more mowing events, and lowest for the class containing two mowing events (Figure IV-6).

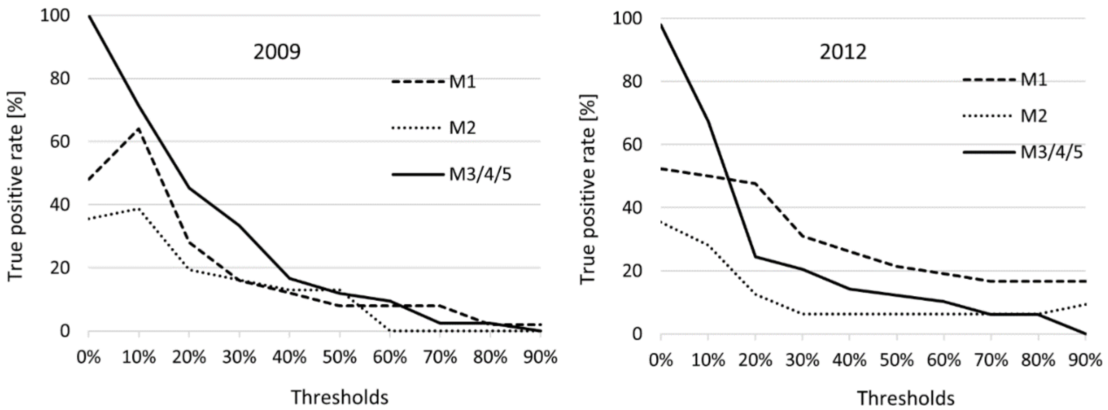

Figure IV-6: Definition of the optimal threshold (0 - 90%) above which a trough was counted as a mowing event (M1 = one mowing event, M2 = two mowing event, M3/4/5 = three or more mowing events) using the true positive rate (modelled mowing events vs. visual interpretation).

Using this threshold, we mapped the four mowing frequency classes across the European Union for each year of the time series. To validate these maps we used a random sample of 300 points from the threshold-free mowing frequency map suggested an overall accuracy of 73% in 2009 and 69% in 2012 (Table IV-1). Producer's and user's accuracy of the class 'no mowing' were highest, ranging between 70% and 100%. In general, the mowing classes showed decreasing accuracies with increasing mowing frequency (Table IV-1).

Table IV-1: Producer's, user's, and overall accuracies of the mowing frequency classes for the years 2009 and 2012, derived by cross checking of 300 modeled mowing points against the normalized NDVI profile and counting the actual troughs by visual interpretation.

Mowing frequency class	*Producer's accuracy*		*User's accuracy*		*Overall accuracy*	
	2009	*2012*	*2009*	*2012*	*2009*	*2012*
No mowing	84.8	79.0	85.2	100.0	73.0	69.4
One mowing event	68.0	73.0	64.0	50.0		
Two mowing events	55.2	45.6	38.7	28.1		
Three or more mowing events	22.4	32.9	71.4	67.1		

Both mowing indices (MI 1 and MI 2) show very similar spatial patterns. On around 90% of the total grassland area in the EU at least one mowing event was detected (around 48% one mowing event, 36% two mowing events, and 16% three or more mowing events). We found a clear east-west divide in grassland-management intensity, with high mowing frequencies (>2 mowing events on average) occurring almost exclusively in Ireland and the United Kingdom (UK), northern France and Spain. Medium frequencies (between 1 and 2 mowing events per year on average) were more widespread in Western Europe (e.g., Ireland, UK, northern and central France, Spain, the Netherland, and southern Italy), but also in some regions in the south of eastern Europe (e.g., Hungary, Romania, and Bulgaria). Lower mowing frequencies (on average <1) occurred all over Europe, but were especially concentrated in the north of Ireland, in the western and northern UK, Germany, the Netherlands and in mountainous regions (e.g., Alps, Pyrenees, Carpathians, and the Massif Central in France; Figure IV-7).

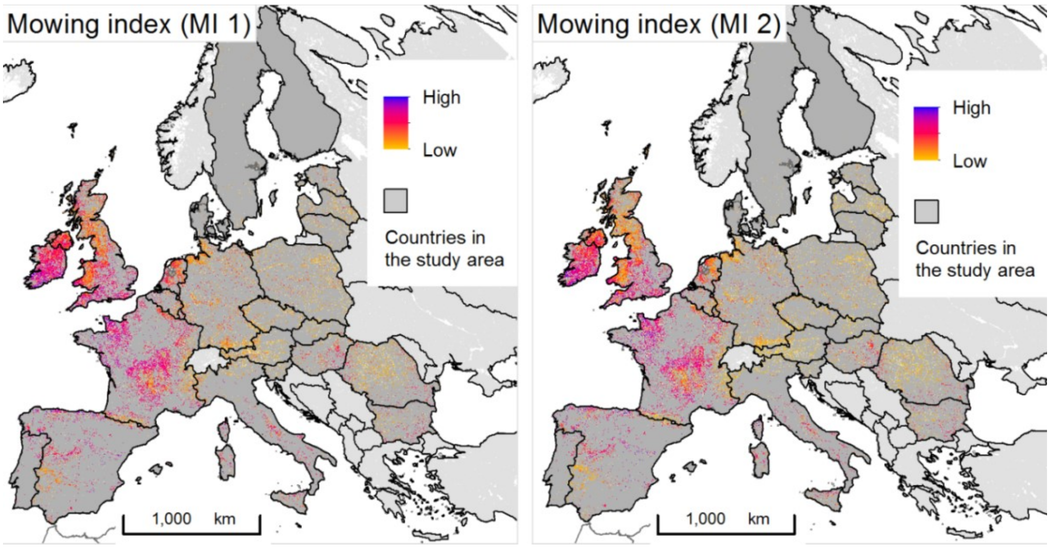

Figure IV-7: Spatial distribution of mowing frequency expressed by mowing indices (MI 1 and MI 2).

Assessing the number of years where at least one active signal was detected, showed that around 98% (44.4 Mha) of the EU's grassland area was managed for at least one year between 2001 and 2012. Around 74% of EUs grasslands were managed in more than six years and 42.1% were managed every year. The latter areas mainly occurred in Ireland, the southern UK, France, Spain, and the Netherlands. Lowest management frequencies (<5 years) were located mainly in mountain regions (e.g., Alps, Pyrenees, and Carpathians) and in Eastern Europe (Figure IV-8).

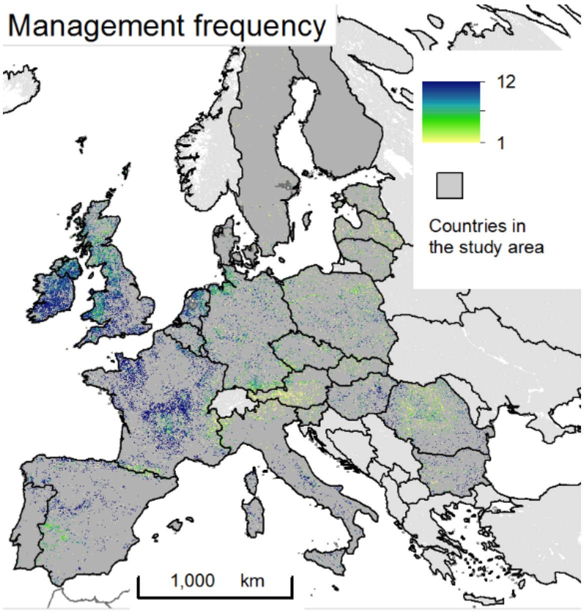

Figure IV-8: Grassland management frequency, defined as the number of managed years from 2001 to 2012.

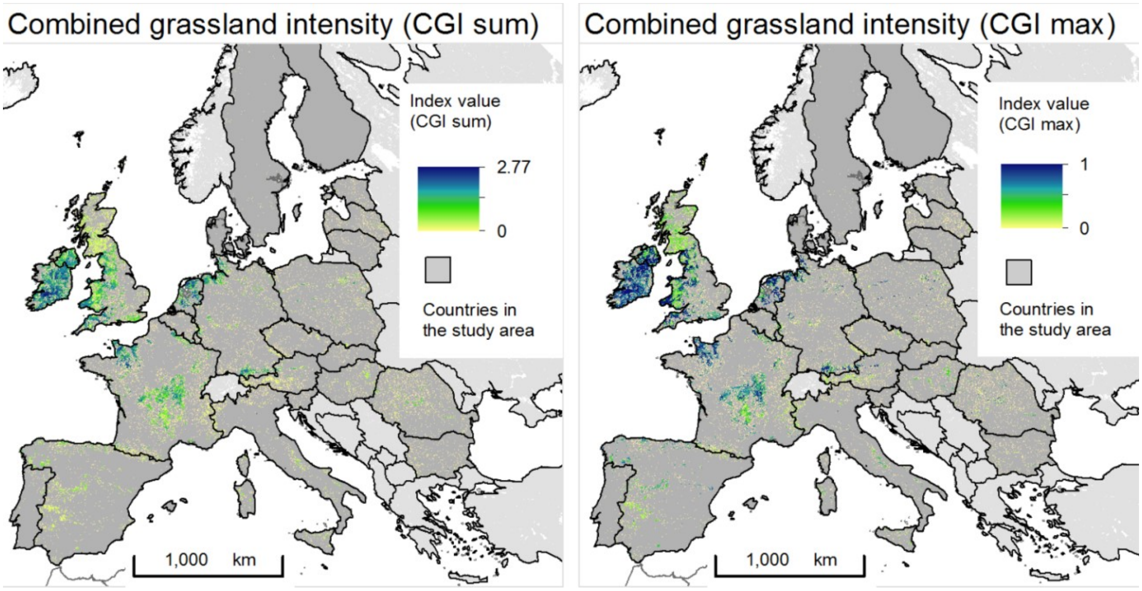

Figure IV-9: Combined grassland intensity indices, calculated by using first the sum (CGI sum) of the normalized indicators mowing index (MI 1), fertilizer application, and livestock density and second only the maximum value of any of the three indicators.

To provide a unified measure of grassland intensity that integrates mowing frequency, fertilizer application and grazing pressure, we generated two grassland management intensity indices CGI_{sum} (assuming the three components are additive) and CGI_{max} (assuming the three components are substitutable in determining intensity) at 3x3-km². Both indices, CGI_{sum} and CGI_{max} resulted in very similar spatial patterns, with highest grassland intensity in Ireland, the Netherlands, northern and central France, northern and southern Germany. Lowest intensity were concentrated in the northern and western UK, central Spain, central

France and in general in mountainous regions (e.g., Alps. Pyrenees, Carpathians, and the Massif Central; Figure IV-9).

Mapping clusters of grassland-management intensity across the EU using SOMs resulted in an optimal number of six clusters. To describe the cluster (C1-C6) characteristics we provided z-scores for all four intensity indicators within the cluster. Positive and negative z-scores highlight the degree of occurrence or absence within the specific cluster for each indicator. Positive and negative numbers, thus, indicate above or below average values, respectively, whereas values close to zero indicate values close to the overall mean of this indicator all over the study area (Figure IV-10).

Cluster 1 was determined by high mowing frequency rates (+0.80) and high grassland management frequency (0.90), but low fertilizer application (-0.64) and livestock density (-73). This cluster occurred mainly in the south of Ireland and UK, central France, northern and central Spain, Hungary, Italy, and the Netherlands. Cluster 2 was mainly determined by indicators above average (+0.40 to +0.80) and was located predominately in Ireland, the western UK and France. Cluster 3 was characterized by averaged mowing frequency (+0.44) and grassland management frequency (+0.37), high fertilizer application (+2.35), and high livestock density (+1.23). This cluster occurred almost exclusively in central Ireland, northern France, and the Netherlands. Cluster 4 had below average values, especially in terms of mowing frequency (-2.05) and grassland management frequency (-1.38). This cluster was mainly located in the Extremadura (Spain), in mountainous regions (e.g., Alps, Pyrenees, Carpathians, and the Massif Central), in eastern Poland, and Latvia. Cluster 5 was determinate by low mowing frequency (-0.35) and fertilizer application (-0.53), yet higher than average rates of livestock density (+0.77). This cluster was widespread, especially in northern Ireland, UK, central France and central Spain. Cluster 6 was characterized by low mowing frequency (-0.55) and grassland management frequency (-0.35), yet relatively high livestock density (+1.01) and fertilizer application (+0.79), and was located mainly in Ireland, western UK, the Netherlands, and Germany (Figure IV-10).

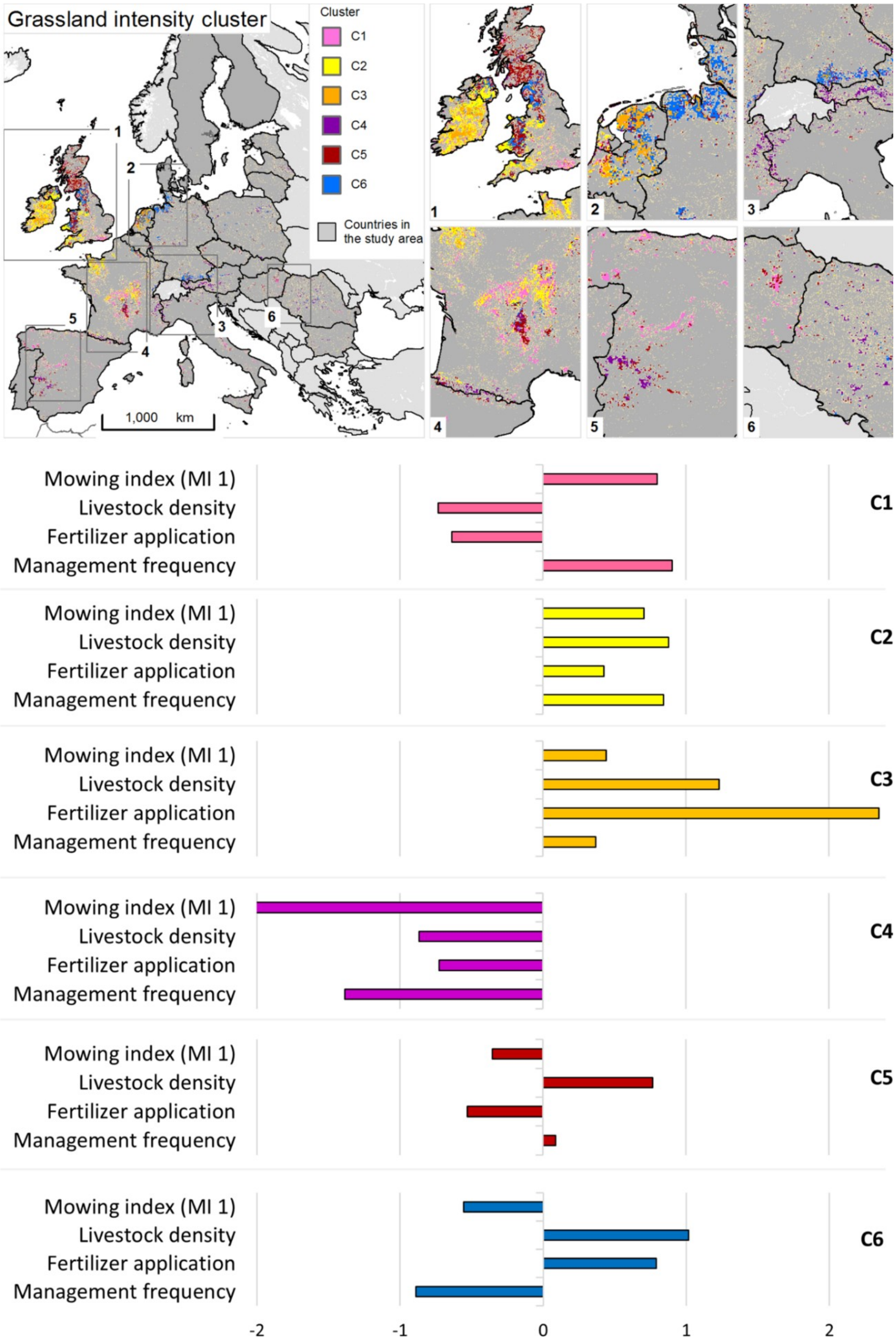

Figure IV-10: Regions of similar grassland management systems mapped using Self-Organizing Maps. Positive and negative z-scores for each indicator showing its degree of occurrence or absence within the specific cluster (C1-C6).

4 Discussion

Spatial patterns in grassland-management intensity are poorly understood, especially at broad geographic scales. Using MODIS NDVI time series we developed a method to map mowing frequency, an important indicator of grassland-management intensity. This method enable to track mowing within a growing season for each year and to combine this with other measures of grassland intensity. Our results provide three different insights into grassland intensity across the EU. First, our annual mowing frequency maps captured up to five mowing events and resulted in two mowing indices. The spatial patterns of these indices match well with grassland productivity gradients derived from national and international agricultural statistics for Europe (Smit et al. 2008). Second, combining a satellite-based mowing index with statistical data on fertilizer application and grazing pressure, we highlighted the diverse spatial patters in management intensity on EU's grasslands. We found a clear east-west divide in management intensity, with high management intensity in western and central Europe, and low-intensity grasslands mainly found in Eastern European regions, but also in mountainous regions and the Extremadura in Spain. These patterns are likely the result of the favorable climate conditions in the Atlantic regions, socio-economic conditions such as rural depopulation (Cramer et al. 2008), marginalization of farmland, and intensification of farming on more favored areas (Gellrich and Zimmermann 2007; Griffiths et al. 2013; MacDonald et al. 2000), structural changes in agricultural sectors triggered by the dissolution of the Eastern Bloc (Lerman 2004; Lerman and Shagaida 2007), lower support for agriculture due to national and/or EU policies (DLG 2005; Niedertscheider et al. 2015), and a slower intensification processes (Jepsen et al. 2015; Rozelle and Swinnen 2004). Third, based on our indicators, we identified six clusters of grassland management, which differed substantially from each other and thus reflect the different land use systems as well as the differences in environmental conditions. These differences have implications for the nature conservation value of the EU's grasslands. Differences in grassland management may at least in part result from EU land-use policies and subsidies that strive to maintain traditional management of grasslands in marginal regions (Fischer et al. 2012; Lefebvre et al. 2012).

4.1 Mapping mowing from satellite images

We carried out one of the first continental scale mapping of mowing based on satellite images. Our partial validation (on the absence or presence of mowing events, not on the frequency) and robustness checks suggest our approach was reliable in separating grasslands that are mown from unmanaged ones Figure VI-5, and our algorithm was able to delineate up to three mowing events. We aggregated all mowing frequencies with five or more mowing events, since the observation of four and five mowing events were very rare Figure IV-6 (for a discussion of uncertainty see below). Our mowing frequency map corresponds well with maps of grassland productivity in Europe (Smit et al. 2008), with more frequent mowing where grassland yields are highest (e.g., in Ireland, the UK, Northern France and the Netherlands). This provides further evidence for a the spatial reorganization of farming that has been going on in Europe since World War II, with an increasing allocation of intensified farming to productive sites, and declining land-use intensity and abandonment in more marginal areas (MacDonald et al. 2000; Strijker 2005).

The most widespread mowing class we found was characterized by a relatively low number of mowing events (84% of all grasslands were mown only one or two times per year), suggesting that most of EU's grasslands are used at relatively low intensity. One reason for this may lie in the growing importance of feed-based on crops, especially oil crops such as maize and soybean (Huyghe et al. 2014). The importance of these crops has increased drastically over the last decades, leading to an increasing displacement of EU's land-use footprint abroad (Kastner et al. 2014). Consistently high mowing frequencies (three or more mowing events per year) occurred mainly in Ireland and southern France, where grasslands are highly productive, and grass-fed livestock is still common (Huyghe et al. 2014). Our analyses also showed that the spatial patterns in mowing frequency, and the grassland management frequency (i.e., number of years with management in 2001-2012) were in general very similar. This suggests grassland management has been relatively stable over the assessed twelve years. This stability also further emphasizes that the most intensive grassland management tends to occur in a few regions in Europe only. These are the grassland rich countries, namely, Ireland, UK, and the Netherlands (Huyghe et al. 2014).

We are not aware of a consistent, European-wide data set specifically documenting mowing practices that could be used to independently validate and inter-compare our results. We, therefore, carried out a number of analyses to build trust in our results, most importantly the comparison of our model results to independently classified ground truth points based on LUCAS. While these comparisons generally attest to the plausibility of our maps, a number of sources of uncertainty, and room for improvement, must be noted. First, we used a conservative grassland mask, including the CORINE classes 'pasture' and 'natural grasslands' and excluding complex mosaic classes containing mosaics of cropland, grassland and woody vegetation. Mapping of mowing in complex mosaics is challenging This is since cropping (and ploughing) results in the same disturbance-type response in NDVI profiles than mowing, and because fields in such mosaic landscapes are typically much smaller than a MODIS pixel size (~5.4 ha). Mosaic classes are particularly widespread in northwestern France, some parts of Belgium and the Netherlands, parts of the Iberia Peninsula, and some Eastern European regions. Therefore, our maps may underestimate grassland management in these areas. Second, we assume an abrupt change in the NDVI profile of grasslands represents mowing, but we cannot fully rule out that other management practices, such as very intensive grazing, result in a mowing signal and are thus captured by our approach. Third, our method based on selecting a threshold that defines when a distance between trough and adjacent peak is considered a mowing event. We used one threshold for the entire EU, and a more regionalized threshold selection would likely improve our mapping. However, a regionalization would require a better ground dataset on mowing events as recently available. Finally, while our algorithm proved to be reliable in separating mown areas from unmanaged ones, the confusion between our mowing classes was substantial, resulting in relatively low user's and producer's accuracies of these classes. One reason for this is the strong seasonality in some regions, which can led to a deep trough especially at the beginning of the growing season, which may not necessarily caused by mowing.

4.2 Patterns of grassland management in Europe

Combining our mowing indices with data on fertilizer application and grazing pressure highlighted distinct patterns of grassland-management intensity. We found high grassland-management intensity in Ireland, UK, France, Germany, and the Netherlands. Conversely, low intensity was found in the Extremadura in Spain, mountainous regions (e.g., Alps, Pyrenees, and Carpathians), and in Eastern Europe. Three factors likely explain these patterns. First, highest grassland intensity occurs in grassland-rich regions with the highest grassland productivity in Europe (Huyghe et al. 2014; Smit et al. 2008), suggesting a concentration on the most productive sites. Second, lower grassland-management intensity was often found in marginal regions that are undergoing rural depopulation due to pull factors from cities (Cramer et al. 2008; Stellmes et al. 2013), that receive lower production support for agriculture (DLG 2005) and where marginal farming conditions hinder an intensive use of existing grassland (e.g., by mechanization) (Gellrich and Zimmermann 2007; Griffiths et al. 2013; MacDonald et al. 2000). Finally, we found a clear east-west divide in grassland-management intensity, which is likely at least in part due to the legacy of socialist management and the dissolution of the Eastern Bloc in 1989 (Lerman 2004; Lerman and Shagaida 2007). Despite substantial intensification efforts during socialism, intensification started later and progressed slower, and many areas in Eastern Europe never reached the level of agricultural industrialization of Western Europe (Jepsen et al. 2015; Niedertscheider et al. 2015; Rozelle and Swinnen 2004). Moreover, substantial cropland abandonment and conversion to grasslands occurred in Eastern Europe during the 1990s (Alcantara et al. 2013; Baumann et al. 2011; Kuemmerle et al. 2008), and many of these lands still are abandoned today (Estel et al. 2015). Finally, while Eastern Europe's farmers now have access to subsidies under the EU's Common Agricultural Policy (CAP), the full effect of these, both in terms of production-oriented payments and agri-environment schemes, has yet to unfold (Niedertscheider et al. 2015; Sutcliffe et al. 2015).

One interesting aspect of our study was the strong similarity between the spatial patterns of our two grassland intensity indices (CGI_{sum} and CGI_{max}). This was surprising, given that CGI_{sum} assumes additivity of the components (i.e., all indicators have to be high to characterize a given region as high-intensity grassland), whereas CGI_{max} requires only one of the components to load high to characterize a region as intensively managed. That both indices showed very similar patterns suggests that regions where at least one intensity indicator is high can be characterized as a region of high management intensity in general. It has to be noted that our three indicators are not fully independent from each other, especially when considering livestock density and fertilizer application rates. High intensity of mowing or grazing are likely also not possible with lower fertilizer intensity (Blüthgen et al. 2012). Furthermore, aggregating our indicators to the 3x3-km² scale could also mean that we blurred differently managed grasslands occurring next to each other. Thus, high values could also indicate mixed systems. Despite this, we found regions, especially across Ireland and southern UK, where only one or two indicators were loading high. This highlights the need to assess grassland-management intensity in a multidimensional way.

4.3 Mapping typical clusters of grassland management

Using SOMs, we found six clusters of similar grassland management systems. Regions classified as Cluster 1 were mainly characterized by fodder production, i.e., frequent mowing but low livestock density as animals are kept in feedlots. Cluster 2 was a mixed system with high mowing frequency and high livestock density, and this cluster occurred mainly in Western Europe. France, Ireland, and United Kingdom in most case with relatively high cattle densities (Robinson et al. 2014). Cluster 3 showed the highest livestock density and fertilizer application, yet relatively low mowing and grassland management frequency, suggesting this cluster was dominated by grasslands on which intensified grazing takes place (e.g., Ireland, Belgium, and the Netherlands). Especially for the Netherland and Belgium where the highest grazing livestock density were reported, whereas Ireland shows in its cluster 3 region a very high cattle density (Robinson et al. 2014). Cluster 4, characterized by low grassland intensity, occurred mainly where water-limitation is prevalent (e.g., Extremadura), but also in Eastern Europe, where lower intensity is likely due to the restructuring of agricultural sectors after the dissolution of the Eastern Bloc (EU 2005; Fischer et al. 2000). This cluster was in general also widespread in mountainous regions, where management intensity is lower due to lower levels of mechanization and an ongoing rural exodus (Gellrich et al. 2007; MacDonald et al. 2000). Thus, cluster 4 seems to coincide heavily with semi-natural, often traditionally managed grasslands of high conservation value (Batáry et al. 2015). Cluster 5 occurred mainly where natural grasslands prevail, according to the CORINE land-cover map 2006. These are areas generally characterized by lower management intensity and similar to cluster 4, may point to grasslands of conservation concern. Finally, cluster 6 was clearly dominated by high livestock density and high fertilizer application, suggesting these grasslands are not used for hay making. For this region (mainly northern Germany) a very high number of pigs per km^2 was documented, whereas in the second hotspot of this cluster in southern Germany cattle breeding is more important (Robinson et al. 2014). Given the differences in management and potential environmental impact among the clusters we identified, different land-use and conservation policies are likely warranted to steer land-systems in these regions towards desirable outcomes, and our clusters may provide a first template for such more regionally targeted policy making.

5 Conclusion

Grasslands play an important role in global food production, provide other important ecosystem services, and support unique biodiversity. Grassland-management intensity affects all of these in major ways, yet despite this, little is known about the intensity of grassland management, especially at broad geographic scales. We developed a MODIS-based mowing indicator and a method to map grassland-management intensity according to the three dimensions of grassland-management intensity: mowing frequency, fertilizer application and grazing pressure. Our results show that spatial patterns of high mowing frequency correspond well with those of high grassland productivity. We revealed diverse spatial patters of grassland-management intensity on EU’s grasslands: high intensity in Ireland, northern and central France, and the Netherlands, and lower intensity in the Extremadura in Spain, western UK, Eastern Europe, and most mountainous regions, likely a result of a spatial reorganization of agriculture to focus on the most productive sites, due to socio-economic changes and legacy-effects from the breakdown of socialism. We also identified six typical clusters of grassland management, reflecting different socio-economic and environmental conditions, and thus likely different impacts of grassland management and different policy levers that would be needed to steer these regions towards desired outcomes. On a methodological level, our analyses highlight how the combination of satellite images and agricultural statistics can help to better assess broad-scale grassland-management intensity and gain a deeper understanding of the multidimensional characteristics of grassland management systems.

Acknowledgements

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Chapter V:
Synthesis

1 Summary

The overarching goal of this doctoral thesis was to deepen our understanding of land-use intenity patterns in agricultural management systems across Europe. In order to be able to do so, the first major objective was to make extensive use of MODIS time series and to generate metrics that improve the mapping quality of land-use intensity. Based on these land-use intensity measures, the second major objective of this doctoral thesis was to identify and characterize spatial patterns and regions of similar cropland and grassland management systems across Europe. This research is timely and needed, since fine scale land-use intensity data are scarce or simply not existent, especially at broad geographic scale. Statistical data are often available only at a national scale and represent snapshots in time, in many cases are not suitable to describe the highly dynamic nature of agricultural management. Quantitative spatially explicit measures of land-use intensity in relation to the different dimensions of land based agricultural production (i.e., input, output, and system properties) are urgently needed to inform land-use and conservation planning. Europe is a prime example to study changes in land-use intensity since most land-use changes today occur along highly diverse gradients of intensification and land- management practices. In the following section, findings of the three core research chapters (Chapter II-IV) are summarized to address the overarching goals mentioned above:

<u>Research question I:</u> *How can the measuring and mapping of land-use intensity be improved using MODIS NDVI time series?*

To reduce the effects of clouds, water, ice, and soil background and to improve the quality of the MODIS NDVI time series, a comprehensive pre-processing chain was carried out. These processing steps are considered to be standard for such data sets. In addition to these steps the NDVI time series were harmonized (i.e., phasing and Min-Max normalization) to account for the strong climate gradients in Europe (e.g., earlier green-up and shifted vegetation peak in the Mediterranean, higher seasonality in the North). The harmonization of the NDVI time series resulted in a substantial improvement of the classification accuracy (>15%) in the subsequent annual classifications. Altogether, the innovative pre-processing routine as well as the extensive use of ground-truth data (LUCAS) resulted in a data set of high quality and accuracy. This is important to note, as all analyses of this doctoral thesis are based on the interpretation of such phenological profiles, which are ultimately a result of different level of land-use intensity and management practices in cropland and grassland management systems.

Throughout Chapter I new methods were developed to derive a wide range of land-use intensity indicators and indices. This includes 12 annual maps from 2001 to 2012 of fallow and active farmland with comparatively high overall accuracies. These maps formed the starting point for a number of important intensity indicators, such as the management frequency (number of years a pixel was actual managed) and fallow cycles (recurring periods of fallow and active cropland). Moreover, by using the time series of active and fallow farmland, it was possible to translate land-use information (i.e., fallow and active) into land-use change processes, such as agricultural land abandonment and recultivation of former abandoned land. Furthermore, in the case of the cropland areas, multi-cropping maps were produced as well as a cropping intensity indicator that take the length of the cropping season into accounts (crop duration ratio). All four cropland intensity indicators were then used to identify regions of similar cropping systems. In case of grassland areas, annual mowing frequencies, an important dimension of grassland-management intensity. From the mowing frequency two mowing indices were calculated which reduce the multi-temporal information to a single index value. By integrating the three dimensions of grassland-management intensity (i.e., mowing frequency, fertilizer application, and grazing pressure) regions of similar grassland management systems were identified and, as a unified measure of grassland-management intensity, two different grassland intensity indices were developed

In sum, the mapped spatial patterns of the intensity indicators and indices as well as the identified regions of similar cropland and grassland systems highlighted how land-use intensity varies in space and time. To date, many of these indicators and indices were the first of their kind available at a continental scale. The results agree well with previous mapping efforts (e.g., Alcantara et al. 2013; Schierhorn et al. 2013) and with those based on agricultural statistics at global or continental scale (e.g., Mueller et al. 2012; Siebert et al. 2010a; Smit et al. 2008). The spatial congruence between our cropping indicators and alternative measures of agricultural management, such as fertilizer and yields, underlines the value of satellite-based indices of a more direct measure of land-use intensity.

<u>Research question II:</u> *What are the spatial patterns of land-use intensity and what are regions of similar agricultural management systems across Europe?*

Using MODIS NDVI time series and agricultural statistics European wide agricultural intensity measures were developed, their spatial patterns and hotspots mapped and similar cropland and grassland management systems identified. Overall, the results highlight the highly diverse spatial patterns in land-use intensity in Europe. These patterns are plausible and show a strong general agreement with existing studies on land-use intensity at global or continental scales. Particularly, the fallow/active farmland maps, the starting point for many subsequent analyses of this doctoral thesis, corresponds well with maps made at global scale or for subsets within our study region (e.g., Alcantara et al. 2013; Schierhorn et al. 2013; Siebert et al. 2010b). The spatial patterns of cropland intensity correspond to patterns of existing maps of cropland net primary production, yields, yield gaps and maps of fertilizer usage (e.g., Monfreda et al. 2008; Mueller et al. 2012; Potter et al. 2010). The spatial patterns of grassland-management intensity match well with mapped patterns of grassland productivity based on national and international census statistics ((e.g., Robinson et al. 2014; Smit et al. 2008). Beside the agreement with existing data sets it is also important to note, that this thesis provides a substantial improvement on the spatial resolution.

The resulting maps show distinct patterns of land-use intensity across Europe throughout all agricultural systems. Areas of permanent fallow land were found mainly in Central and Eastern Europe, but also in Europe's mountainous regions (i.e., Alps, and Pyrenees). Since the majority of permanent fallow land are located in the area of the former Eastern Bloc (former USSR-aligned countries) these areas can be linked to abandonment that occurred due to the agriculture reorganization after the dissolution of the Eastern Bloc in 1989. Abandonment is an ongoing land-change process in Europe and is widespread in Eastern Europe (e.g., northeastern Poland), but also in southern Scandinavia, and Europe's mountainous regions. The abandonment of agricultural land can be explained in most cases by a combination of socio-economic and environmental factors, including rural depopulation, lower production support for agriculture, marginalization of agricultural land in remote and mountain regions, and a concentration of farming on more productive and accessible sites. However, the rates of abandonment have slowed down in recent years. The opposite process of abandonment, the recultivation of formerly abandoned land, is increasingly common in former states of the Eastern Bloc (e.g., European Russia, or the Balkans). This process is partially a result of the eastward expansion of the EU with subsequent changes in land-use policies; but it is also due to the growing global demand for agricultural products (e.g., food, feed and biofuel). Moderate fallow frequencies occurred in central European countries, including Germany, Poland, and Czech Republic, as well as in

Ireland and the UK. Fallow cycles are common in water-limited regions but also in some regions in Eastern Europe (e.g., Iberian Peninsula, northern Ukraine, Russia, and some Mediterranean areas). The lowest fallow frequencies occurred mainly in Western Europe (e.g., UK, and France), large parts of the Mediterranean region, and in the Black Earth Region (i.e., Chernozem). Accordingly, these areas correspond with higher rates of multi-cropping, often combined with longer crop duration, and high mowing frequencies. The interpretation of multiple land-use intensity indicators requires advanced algorithms, which reduce the complexity of multiple data sets without to lose information. This was achieved by using self-organizing maps (SOMs). SOMs enabled the identification of six regions of similar management systems for cropland and grassland systems. These clusters can be linked to different agro-environmental and socio-economic conditions across Europe. For example, each of the six cropland clusters were related to areas of highly favorable agro-environmental conditions, such as humidity (e.g., in Germany, and Denmark) and soil fertility (e.g., in southern Russia, and the Ukraine). Another cluster was linked to irrigated areas (e.g., the Ebro-basin in northern Spain, or the Black Sea area). Clusters corresponded also to management practices as multi-cropping (e.g., in southern Russia, and northern Germany) and fallow land in water-limited regions (e.g., Extremadura, and northern Andalusia in Spain, southern Portugal). Some clusters referred to regions without major constrains but not used to their full potential. These clusters are mainly located in Central and Eastern Europe and are characterized by higher fallow frequencies, which are likely the result of the restructuring of agricultural sectors after the dissolution of the Eastern Bloc. Similar clusters can be found in mountainous regions (i.e. marginal areas). Clusters with the highest grassland-management intensity in the EU occurred in grassland-rich regions with favorable climate conditions and correlates accordingly with the highest grassland productivity in Europe (i.e., Atlantic regions). Such grassland clusters refer to regions of mixed systems, characterized by high rates of mowing and relatively high cattle densities (e.g., France, Ireland, and UK), intensified grazing (e.g., Ireland, Belgium, and the Netherlands), or not used for hay making but dominated by high livestock density and high fertilizer application (e.g., northern and southern Germany). Lower grassland-management intensity was mostly found in remote and marginal regions. Those regions were characterized by unfavorable farming conditions that hinder intensive use (e.g., by mechanization) and lower production support for of existing grassland. Another typical cluster was characterized by water limitations (e.g., in the Extremadura region in Spain), in mountainous regions, and in some regions in Eastern Europe. Other clusters occurred in natural grasslands (e.g., UK) indicating a lower land-use intensity. Such areas may provide interesting target regions for grassland conservation schemes.

In sum, this study revealed distinctly different spatial patterns of land-use intensity across European, with high management intensity in Western and Central Europe and the Mediterranean region, and low intensity or abandoned farmland mainly found in Eastern Europe, mountainous regions, and the Extremadura in Spain. Recultivation of former abanoned land occurred mainly in Eastern Europe and has become an important land change process. These primary spatial patterns can be explained by agro-environmental and socio-economic conditions.

2 Conclusions

Mapping land-use intensity is essential to improve our understanding of agricultural management systems and their environmental and social outcomes. As fertile land become scarcer and the demand for resources continues to increase, the competition over land will escalate. This is particularly true when considering the increasing number of land uses that are not food-production oriented, such as carbon storage or conservation. The negative environmental effects associated with further expansion of agricultural production into natural areas, will most likely not remain feasible to provide sufficient increases to meet future agricultural production demands. One alternative to increase production is the sustainable intensification of existing production systems. However, until now we do not know much about land-use intensity and its spatial pattern, as the discipline of land-use science has mainly focused on broad land-cover conversions. As a result, for most world regions, the spatial patterns of cropland- and grassland-management intensity remain highly unclear. One reason for the missing land-use intensity information is the lack of input data, especially for larger regions. Using MODIS NDVI time series combined with statistical data on fertilizer application and livestock density, this work provides new ways to characterize land-change processes along with a wide range of land-use intensity metrics. The methodological backbone of this work consists of a suite of advanced algorithms including Random Forest classification, SPLITS, and SOMs.

Most of these metrics have not been implemented across larger regions and thus form one of the major contributions of this doctoral thesis. Based on remote-sensing observations this work provides: (1) the first Pan-European map of active and fallow farmland and new concepts of abandonment and recultivation, (2) the first map of fallowing patterns at large scale, and (3) the first large-scale map of mowing frequency, which allow a comprehensive assessment of the three main dimensions of grassland-management intensity. These indicators were used to derive further metrics, such as mowing indices, and, in combination with statistical data (i.e., fertilizer application and livestock density) grassland intensity indices and regions of similar management systems. The clustering approach (SOMs) allow assessing land-use intensity in a multidimensional way, using a suite of indicators rather than only a single measure.The results highlight the opportunities that arise by combining MODIS data and statistical data to generate agricultural intensity metrics. Most of the indicators developed here refer to at least one of the three dimensions of the land based agricultural production (i.e., input, output, and system properties) and therefore ultimately improve assessments of the complex and multidimensional phenomenon of land-use intensity. A further goal of this work was to provide insights into the diverse spatial patterns of land-use intensity and the wide range of agricultural systems across Europe. The analyses refer to the pan-European croplands and the EU's grassland systems. These systems range from traditional small-scale farming to large-scale agri-business farmlands. Resulting patterns are a consequence of a long agricultural history and large environmental, political, and socio-economic differences across the continent during the last century. Specifically, Europe has experienced two different economic systems until the dissolution of the Eastern Bloc in 1989. The legacy of this east west divide remains visible in today's landscape and the corresponding spatial patterns mapped in this work. The vast majority of farmland abandonment was found in Eastern Europe, but at the same time former abandoned land in areas of favorable agricultural conditions were recultivated (e.g., Chernozem region). Western Europe is also facing rural depopulation and marginalization of farmland, especially in remote areas, expressed by higher abandonment and fallow rates in these regions. Western Europe shows an overall higher agricultural intensity compared to regions in Eastern Europe, expressed by overall less frequent and lower proportions of fallow land, and a higher number of harvests per year. This is likely a result of the higher and longer-running support of agriculture by EU's subsidies, and a shift in policies towards larger amounts of biofuel. This indicates that Europe currently experiences a number of different, often diverging land-use intensity changes. Land-use intensity in Europe is not only driven by socio-economic conditions. The fallow patterns in the Extremadura (Spain), the highly intensive multi-cropping area in the South of Ukraine and European Russia as well as the highly productive grassland areas were caused by agro-environmental conditions, which underline climate dependence as another important dimension of land-use intensity.

This work highlights the necessity to assess land-use intensity in a multidimensional way using a suite of intensity metrics and emphasizes the role that satellite based monitoring can play in assessing land-use intensity across large scales. The wide range of new methods and agricultural intensity metrics developed in the context of this doctoral thesis contribute well to the growing need for frequent monitoring of agricultural lands in order to assess the environmental outcomes in space and time. The methodologies developed here can potentially be broadly applied and updated annually. Not least, this work has shown that remote sensing data can be combined with statistical data in a meaningful way, which further extends the possible applications of the indicator data sets. The mapping of similar agricultural systems may help to identify potential candidate regions for sustainable intensification of agricultural land. The outcomes of this work deepen the understanding of land-use intensity in agricultural management systems and therefore, can help to solve major issues regarding improved land management systems.

References

Aide, T.M., & Grau, H.R. (2004). Globalization, Migration, and Latin American Ecosystems. *Science, 305*, 1915-1916

Alcantara, C., Kuemmerle, T., Baumann, M., Bragina, E.V., Griffiths, P., Hostert, P., Knorn, J., Müller, D., Prishchepov, A.V., Schierhorn, F., Sieber, A., & Radeloff, V.C. (2013). Mapping the extent of abandoned farmland in Central and Eastern Europe using MODIS time series satellite data. *Environmental Research Letters, 8*

Alcantara, C., Kuemmerle, T., Prishchepov, A.V., & Radeloff, V.C. (2012). Mapping abandoned agriculture with multi-temporal MODIS satellite data. *Remote Sensing of Environment, 124*, 334-347

Allan, E., Bossdorf, O., Dormann, C.F., Prati, D., Gossner, M.M., Tscharntke, T., Blüthgen, N., Bellach, M., Birkhofer, K., Boch, S., Böhm, S., Börschig, C., Chatzinotas, A., Christ, S., Daniel, R., Diekötter, T., Fischer, C., Friedl, T., Glaser, K., Hallmann, C., Hodac, L., Hölzel, N., Jung, K., Klein, A.M., Klaus, V.H., Kleinebecker, T., Krauss, J., Lange, M., Morris, E.K., Müller, J., Nacke, H., Pašalić, E., Rillig, M.C., Rothenwöhrer, C., Schall, P., Scherber, C., Schulze, W., Socher, S.A., Steckel, J., Steffan-Dewenter, I., Türke, M., Weiner, C.N., Werner, M., Westphal, C., Wolters, V., Wubet, T., Gockel, S., Gorke, M., Hemp, A., Renner, S.C., Schöning, I., Pfeiffer, S., König-Ries, B., Buscot, F., Linsenmair, K.E., Schulze, E.-D., Weisser, W.W., & Fischer, M. (2014). Interannual variation in land-use intensity enhances grassland multidiversity. *Proceedings of the National Academy of Sciences, 111*, 308-313

Angelstam, P., Boresjö-Bronge, L., Mikusiński, G., Sporrong, U., & Wästfelt, A. (2003). Assessing village authenticity with satellite images: a method to identify intact cultural landscapes in Europe. *AMBIO, 32*, 594-604

Anselin, L. (1995). Local Indicators of Spatial Association—LISA. *Geographical Analysis, 27*, 93-115

Anselin, L., Syabri, I., & Kho, Y. (2010). GeoDa: An Introduction to Spatial Data Analysis. In M.M. Fischer, & A. Getis (Eds.), *Handbook of Applied Spatial Analysis* (pp. 73-89): Springer Berlin Heidelberg

Asam, S., Klein, D., & Dech, S. (2015). Estimation of grassland use intensities based on high spatial resolution LAI time series. In, *36th International Symposium on Remote Sensing of Environment*. Berlin: The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences

Bajzelj, B., Richards, K.S., Allwood, J.M., Smith, P., Dennis, J.S., Curmi, E., & Gilligan, C.A. (2014). Importance of food-demand management for climate mitigation. *Nature Clim. Change, 4*, 924-929

Baldock, D., Beaufoy, G., Clark, J., Institute for European Environmental, P., World Wide Fund for, N., & Joint Nature Conservation, C. (1994). *The nature of farming: low intensity farming systems in nine European countries*. London: Institute for European Environmental Policy

Barriopedro, D., Fischer, E.M., Luterbacher, J., Trigo, R.M., & García-Herrera, R. (2011). The Hot Summer of 2010: Redrawing the Temperature Record Map of Europe. *Science, 332*, 220-224

Batáry, P., Dicks, L.V., Kleijn, D., & Sutherland, W.J. (2015). The role of agri-environment schemes in conservation and environmental management. *Conservation Biology, 29*, 1006-1016

Baumann, M., Kuemmerle, T., Elbakidze, M., Ozdogan, M., Radeloff, V.C., Keuler, N.S., Prishchepov, A.V., Kruhlov, I., & Hostert, P. (2011). Patterns and drivers of post-socialist farmland abandonment in Western Ukraine. *Land Use Policy, 28*, 552-562

Beringer, T., Lucht, W., & Schaphoff, S. (2011). Bioenergy production potential of global biomass plantations under environmental and agricultural constraints. *GCB Bioenergy, 3*, 299-312

Bernhardt-Römermann, M., Römermann, C., Sperlich, S., & Schmidt, W. (2011). Explaining grassland biomass – the contribution of climate, species and functional diversity depends on fertilization and mowing frequency. *Journal of Applied Ecology, 48*, 1088-1097

Biradar, C.M., & Xiao, X. (2011). Quantifying the area and spatial distribution of double- and triple-cropping croplands in India with multi-temporal MODIS imagery in 2005. *International Journal of Remote Sensing, 32*, 367-386

Blengini, G.A., & Busto, M. (2009). The life cycle of rice: LCA of alternative agri-food chain management systems in Vercelli (Italy). *Journal of Environmental Management, 90*, 1512-1522

Blüthgen, N., Dormann, C.F., Prati, D., Klaus, V.H., Kleinebecker, T., Hölzel, N., Alt, F., Boch, S., Gockel, S., Hemp, A., Müller, J., Nieschulze, J., Renner, S.C., Schöning, I., Schumacher, U., Socher, S.A., Wells, K., Birkhofer, K., Buscot, F., Oelmann, Y., Rothenwöhrer, C., Scherber, C., Tscharntke, T., Weiner, C.N., Fischer, M., Kalko, E.K.V., Linsenmair, K.E., Schulze, E.-D., & Weisser, W.W. (2012). A quantitative index of land-use intensity in grasslands: Integrating mowing, grazing and fertilization. *Basic and Applied Ecology, 13*, 207-220

Boellstorff, D., & Benito, G. (2005). Impacts of set-aside policy on the risk of soil erosion in central Spain. *Agriculture, Ecosystems & Environment, 107*, 231-243

Bontemps, S., Defournya, P., Van Bogaert, E., Weber, J.-L., & Arino, O. (2009). GlobCorine–A joint EEA-ESA project for operational land dynamics monitoring at pan-European scale. In, *The 33rd International Symposium on Remote Sensing of Environment*. Tucson/Arizona, USA

Bradley, B.A., Jacob, R.W., Hermance, J.F., & Mustard, J.F. (2007). A curve fitting procedure to derive inter-annual phenologies from time series of noisy satellite NDVI data. *Remote Sensing of Environment, 106*, 137-145

Breiman, L. (2001). Random Forests. *Machine Learning, 45*, 5-32

Burney, J.A., Davis, S.J., & Lobell, D.B. (2010). Greenhouse gas mitigation by agricultural intensification. *Proceedings of the National Academy of Sciences, 107*, 12052-12057

Butchart, S.H.M., Walpole, M., Collen, B., van Strien, A., Scharlemann, J.P.W., Almond, R.E.A., Baillie, J.E.M., Bomhard, B., Brown, C., Bruno, J., Carpenter, K.E., Carr, G.M., Chanson, J., Chenery, A.M., Csirke, J., Davidson, N.C., Dentener, F., Foster, M., Galli, A., Galloway, J.N., Genovesi, P., Gregory, R.D., Hockings, M., Kapos, V., Lamarque, J.-F., Leverington, F., Loh, J., McGeoch, M.A., McRae, L., Minasyan, A., Morcillo, M.H., Oldfield, T.E.E., Pauly, D., Quader, S., Revenga, C., Sauer, J.R., Skolnik, B., Spear, D., Stanwell-Smith, D., Stuart, S.N., Symes, A., Tierney, M., Tyrrell, T.D., Vié, J.-C., & Watson, R. (2010). Global Biodiversity: Indicators of Recent Declines. *Science, 328*, 1164-1168

Campbell, J.E., Lobell, D.B., Genova, R.C., & Field, C.B. (2008). The Global Potential of Bioenergy on Abandoned Agriculture Lands. *Environmental Science & Technology, 42*, 5791-5794

Card, D.H. (1982). Using known map category marginal frequencies to improve estimates of thematic map accuracy. *Photogrammetric Engineering and Remote Sensing, 48*, 431-439

Carroll, M.L., Townshend, J.R., DiMiceli, C.M., Noojipady, P., & Sohlberg, R.A. (2009). A new global raster water mask at 250 m resolution. *International Journal of Digital Earth, 2*, 291-308

Ciais, P., Reichstein, M., Viovy, N., Granier, A., Ogee, J., Allard, V., Aubinet, M., Buchmann, N., Bernhofer, C., Carrara, A., Chevallier, F., De Noblet, N., Friend, A.D., Friedlingstein, P., Grunwald, T., Heinesch, B., Keronen, P., Knohl, A., Krinner, G., Loustau, D., Manca, G., Matteucci, G., Miglietta, F., Ourcival, J.M., Papale, D., Pilegaard, K., Rambal, S., Seufert, G., Soussana, J.F., Sanz, M.J., Schulze, E.D., Vesala, T., & Valentini, R. (2005). Europe-wide reduction in primary productivity caused by the heat and drought in 2003. *Nature, 437*, 529-533

Clark, M.L., Aide, T.M., & Riner, G. (2012). Land change for all municipalities in Latin America and the Caribbean assessed from 250-m MODIS imagery (2001–2010). *Remote Sensing of Environment, 126*, 84-103

Cohen, W.B., Yang, Z., & Kennedy, R. (2010). Detecting trends in forest disturbance and recovery using yearly Landsat time series: 2. TimeSync — Tools for calibration and validation. *Remote Sensing of Environment, 114*, 2911-2924

Cooper, T., Baldock, D., Rayment, M., Kuhmonen,T., Terluin, I., Swales, V., Poux, X., Zakeossian, D. and Farmer, M. (2006). An Evaluation of the less favoured area measure in the 25 member states of the European Union. *IEEP*

Cramer, V.A., Hobbs, R.J., & Standish, R.J. (2008). What's new about old fields? Land abandonment and ecosystem assembly. *Trends in Ecology & Evolution, 23*, 104-112

Cremene, C., Groza, G., Rakosy, L., Schileyko, A.A., Baur, A., Erhardt, A., & Baur, B. (2005). Alterations of Steppe-Like Grasslands in Eastern Europe: a Threat to Regional Biodiversity Hotspots. *Conservation Biology, 19*, 1606-1618

Davies, D.L., & Bouldin, D.W. (1979). A Cluster Separation Measure. *IEEE Transactions on Pattern Analysis and Machine Intelligence, PAMI-1*, 224-227

de Beurs, K.M., Henebry, G.M., & Gitelson, A.A. (2004). Regional MODIS analysis of abandoned agricultural lands in the Kazakh steppes. In, *Geoscience and Remote Sensing Symposium, 2004. IGARSS '04. Proceedings. 2004 IEEE International* (pp. 739-741) de Beurs, K.M., & Ioffe, G. (2013). Use of Landsat and MODIS data to remotely estimate Russia's sown area. *Journal of Land Use Science*, 1-25

de Boor, C.A.p.g.t.s. (2001). *A Practical Guide to Splines*. New York: Springer

Defourny, P., Bontemps, S., van Bogaert. E., Weber, J.L., & Soukup, T. (2010). GlobCorine Validation Report. In. http://due.esrin.esa.int/files/p114/GLOBCORINE_VR_2.1_20100406.pdf (accessed 24/03/2015)

DeFries, R.S., Foley, J.A., & Asner, G.P. (2004). Land-use choices: balancing human needs and ecosystem function. *Frontiers in Ecology and the Environment, 2*, 249-257

DeFries, R.S., Houghton, R.A., Hansen, M.C., Field, C.B., Skole, D., & Townshend, J. (2002). Carbon emissions from tropical deforestation and regrowth based on satellite observations for the 1980s and 1990s. *Proceedings of the National Academy of Sciences, 99*, 14256-14261

Delincé, J. (2001). A European approach to area frame survey. In, *Proceedings of the Conference on Agricultural and Environmental Statistical Applications in Rome* (pp. 463-472). Rome

Dengler, J., Janišová, M., Török, P., & Wellstein, C. (2014). Biodiversity of Palaearctic grasslands: a synthesis. *Agriculture, Ecosystems & Environment, 182*, 1-14

DLG (2005). Land Abandonment, Biodiversity and the CAP Outcome of an international seminar in Sigulda , Latvia, 7–8 October, 2004.

Dorais, A., & Cardille, J. (2011). Strategies for Incorporating High-Resolution Google Earth Databases to Guide and Validate Classifications: Understanding Deforestation in Borneo. *Remote Sensing, 3*, 1157-1176

EEA (2011). CORINE Land Cover 2006 (250m), http://www.eea.europa.eu/data-and-maps/data/corine-land-cover-2006-raster-3#tab-gis-data (assessed 03.06.2014)

Ellis, E.C., Kaplan, J.O., Fuller, D.Q., Vavrus, S., Klein Goldewijk, K., & Verburg, P.H. (2013). Used planet: A global history. *Proceedings of the National Academy of Sciences*

Ellis, E.C., & Ramankutty, N. (2007). Putting people in the map: anthropogenic biomes of the world. *Frontiers in Ecology and the Environment, 6*, 439-447

Erb, K.-H., Haberl, H., Jepsen, M.R., Kuemmerle, T., Lindner, M., Müller, D., Verburg, P.H., & Reenberg, A. (2013). A conceptual framework for analysing and measuring land-use intensity. *Current Opinion in Environmental Sustainability, 5*, 464-470

Erb, K.-H., Haberl, H., Krausmann, F., Lauk, C., Plutzar, C., Steinberger, J.K., Müller, C., Bondeau, A., Waha, K., & Pollack, G. (2009). Eating the Planet: Feeding and fuelling the world sustainably, fairly and humanely– a scoping study Social Ecology Working Paper 116. Vienna: Institute of Social Ecology.

Estel, S., Kuemmerle, T., Alcántara, C., Levers, C., Prishchepov, A., & Hostert, P. (2015). Mapping farmland abandonment and recultivation across Europe using MODIS NDVI time series. *Remote Sensing of Environment, 163*, 312-325

EU (2005). *Soil atlas of Europe*. Luxembourg: European Communities

Eurostat (2010). LUCAS - a multi-purpose land use survey." Sigma - The Bulletin of European Statistics 2010/01

Eurostat (2014a). Land cover/use statistics (LUCAS), http://ec.europa.eu/eurostat/web/lucas/overview (accessed 24.03.15)

Eurostat (2014b). Regional Agriculture Statistics, http://ec.europa.eu/eurostat/data/database (assessed 24.03.2015)

Fang, H., Liang, S., & Hoogenboom, G. (2011). Integration of MODIS LAI and vegetation index products with the CSM–CERES–Maize model for corn yield estimation. *International Journal of Remote Sensing, 32*, 1039-1065

FAO (2005). *Grasslands of the world*. http://www.fao.org/docrep/008/y8344e/y8344e00.htm: Agriculture and Consumer Protection

FAO (2006). *Livestock's long shadow: environmental issues and options*. Rome: Food and Agriculture Organization of the United Nations (FAO)

FAO (2007). Gridded livestock of the world 2007. In W. Wint, Robinson, T. (Ed.). Rome, pp 131

FAO (2014). FAOSTAT, Methods & Standards, http://faostat3.fao.org/mes/glossary/E (accessed 24.03.15)

FAO/EC/ISRIC (2003). World Soil Resources. In. http://fao.org/soilsportal/soil-survey/soil-maps-and-databases/en/: FAO (accessed 15/04/2015)

Fischer, G., Velthuizen, v.H., & Nachtergaele, F.O. (2000). IIASA Interim Report IR-00-064 - Global Agro-Ecological Zones Assessment: Methodology and Results. In. http://www.iiasa.ac.at/publication/more_IR-00-064.php: International Institute for Applied Systems Analysis (IIASA)

Fischer, J., Hartel, T., & Kuemmerle, T. (2012). Conservation policy in traditional farming landscapes. *Conservation Letters, 5*, 167-175

Fisher, J., Mustard, J., & Vadeboncoeur, M. (2006). Green leaf phenology at Landsat resolution: Scaling from the field to the satellite. *Remote Sensing of Environment, 100*, 265-279

Foley, J.A., DeFries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J.A., Prentice, I.C., Ramankutty, N., & Snyder, P.K. (2005). Global Consequences of Land Use. *Science, 309*, 570-574

Foley, J.A., Ramankutty, N., Brauman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M., Mueller, N.D., O/'Connell, C., Ray, D.K., West, P.C., Balzer, C., Bennett, E.M., Carpenter, S.R., Hill, J., Monfreda, C., Polasky, S., Rockstrom, J., Sheehan, J., Siebert, S., Tilman, D., & Zaks, D.P.M. (2011). Solutions for a cultivated planet. *Nature, 478*, 337-342

Foody, G.M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment, 80*, 185-201

Foody, G.M. (2008). Harshness in image classification accuracy assessment. *International Journal of Remote Sensing, 29*, 3137-3158

Foody, G.M. (2010). Assessing the accuracy of land cover change with imperfect ground reference data. *Remote Sensing of Environment, 114*, 2271-2285

Foody, G.M., & Boyd, D.S. (2013). Using Volunteered Data in Land Cover Map Validation: Mapping West African Forests. *Selected Topics in Applied Earth Observations and Remote Sensing, IEEE Journal of, 6*, 1305-1312

Friedl, M.A., Sulla-Menashe, D., Tan, B., Schneider, A., Ramankutty, N., Sibley, A., & Huang, X. (2010). MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets. *Remote Sensing of Environment, 114*, 168-182

Fritz, S., See, L., McCallum, I., Schill, C., Obersteiner, M., van der Velde, M., Boettcher, H., Havlík, P., & Achard, F. (2011). Highlighting continued uncertainty in global land cover maps for the user community. *Environmental Research Letters, 6*

Fritz, S., See, L., McCallum, I., You, L., Bun, A., Moltchanova, E., Duerauer, M., Albrecht, F., Schill, C., Perger, C., Havlik, P., Mosnier, A., Thornton, P., Wood-Sichra, U., Herrero, M., Becker-Reshef, I., Justice, C., Hansen, M., Gong, P., Abdel Aziz, S., Cipriani, A., Cumani, R., Cecchi, G., Conchedda, G., Ferreira, S., Gomez, A., Haffani, M., Kayitakire, F., Malanding, J., Mueller, R., Newby, T., Nonguierma, A., Olusegun, A., Ortner, S., Rajak, D.R., Rocha, J., Schepaschenko, D., Schepaschenko, M., Terekhov, A., Tiangwa, A., Vancutsem, C., Vintrou, E., Wenbin, W., van der Velde, M., Dunwoody, A., Kraxner, F., & Obersteiner, M. (2015). Mapping global cropland and field size. *Global Change Biology, 21*, 1980-1992

Fritz, S., See, L., You, L., Justice, C., Becker-Reshef, I., Bydekerke, L., Cumani, R., Defourny, P., Erb, K., Foley, J., Gilliams, S., Gong, P., Hansen, M., Hertel, T., Herold, M., Herrero, M., Kayitakire, F., Latham, J., Leo, O., McCallum, I., Obersteiner, M., Ramankutty, N., Rocha, J., Tang, H., Thornton, P., Vancutsem, C., van der Velde, M., Wood, S., & Woodcock, C. (2013). The Need for Improved Maps of Global Cropland. *Eos, Transactions American Geophysical Union, 94*, 31-32

Galford, G.L., Mustard, J.F., Melillo, J., Gendrin, A., Cerri, C.C., & Cerri, C.E.P. (2008). Wavelet analysis of MODIS time series to detect expansion and intensification of row-crop agriculture in Brazil. *Remote Sensing of Environment, 112*, 576-587

Gallaun, H., Zanchi, G., Nabuurs, G.-J., Hengeveld, G., Schardt, M., & Verkerk, P.J. (2010). EU-wide maps of growing stock and above-ground biomass in forests based on remote sensing and field measurements. *Forest Ecology and Management, 260*, 252-261

Gallego, J., & Delincé, J. (2010). The European Land Use and Cover Area-Frame Statistical Survey. *Agricultural Survey Methods* (pp. 149-168): John Wiley & Sons, Ltd

Ganguly, S., Friedl, M.A., Tan, B., Zhang, X., & Verma, M. (2010). Land surface phenology from MODIS: Characterization of the Collection 5 global land cover dynamics product. *Remote Sensing of Environment, 114*, 1805-1816

García-Ruiz, J.M., & Lana-Renault, N. (2011). Hydrological and erosive consequences of farmland abandonment in Europe, with special reference to the Mediterranean region – A review. *Agriculture, Ecosystems & Environment, 140*, 317-338

Garnett, T., Appleby, M.C., Balmford, A., Bateman, I.J., Benton, T.G., Bloomer, P., Burlingame, B., Dawkins, M., Dolan, L., Fraser, D., Herrero, M., Hoffmann, I., Smith, P., Thornton, P.K., Toulmin, C., Vermeulen, S.J., & Godfray, H.C.J. (2013a). Sustainable Intensification in Agriculture: Premises and Policies. *Science, 341*, 33-34

Garnett, T., Appleby, M.C., Balmford, A., Bateman, I.J., Benton, T.G., Bloomer, P., Burlingame, B., Dawkins, M., Dolan, L., Fraser, D., & others (2013b). Sustainable intensification in agriculture: premises and policies. *Science, 341*, 33-34

Gellrich, M., Baur, P., Koch, B., & Zimmermann, N.E. (2007). Agricultural land abandonment and natural forest re-growth in the Swiss mountains: A spatially explicit economic analysis. *Agriculture, Ecosystems & Environment, 118*, 93-108

Gellrich, M., & Zimmermann, N.E. (2007). Investigating the regional-scale pattern of agricultural land abandonment in the Swiss mountains: A spatial statistical modelling approach. *Landscape and Urban Planning, 79*, 65-76

Gienapp, C., Sanftleben, P., Jennerich, H.J., & Heilmann, H. (2012). Beiträge zur Weizenproduktion In, *Mitteilungen der Landesforschungsanstalt für Landwirtschaft und Fischerei*. http://www.landwirtschaft-mv.de/cms2/LFA_prod/LFA/content/de/_Service/Mitteilungen_der_LFA/Heft_47/index.jsp: Landesforschungsanstalt für Landwirtschaft und Fischerei,

Dorfplatz 1, 18276 Gülzow

Gislason, P.O., Benediktsson, J.A., & Sveinsson, J.R. (2006). Random Forests for land cover classification. *Pattern Recognition Letters, 27*, 294-300

Gobron, N., Pinty, B., Mélin, F., Taberner, M., Verstraete, M.M., Belward, A., Lavergne, T., & Widlowski, J.L. (2005). The state of vegetation in Europe following the 2003 drought. *International Journal of Remote Sensing, 26*, 2013-2020

Godfray, H.C.J., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F., Pretty, J., Robinson, S., Thomas, S.M., & Toulmin, C. (2010). Food Security: The Challenge of Feeding 9 Billion People. *Science, 327*, 812-818

Griffiths, P., Müller, D., Kuemmerle, T., & Hostert, P. (2013). Agricultural land change in the Carpathian ecoregion after the breakdown of socialism and expansion of the European Union. *Environmental Research Letters, 8*

Grigg, D. (1979). Ester Boserups theory of agrarian change: a critical review. *Progress in Human Geography, 3*, 64-84

Haberl, H., Erb, K.H., Krausmann, F., Gaube, V., Bondeau, A., Plutzar, C., Gingrich, S., Lucht, W., & Fischer-Kowalski, M. (2007). Quantifying and mapping the human appropriation of net primary production in earth's terrestrial ecosystems. *Proceedings of the National Academy of Sciences, 104*, 12942-12947

Haberl, H., Steinberger, J.K., Plutzar, C., Erb, K.-H., Gaube, V., Gingrich, S., & Krausmann, F. (2012). Natural and socioeconomic determinants of the embodied human appropriation of net primary production and its relation to other resource use indicators. *Ecological Indicators, 23*, 222-231

Hartvigsen, M. (2014). Land reform and land fragmentation in Central and Eastern Europe. *Land Use Policy, 36*, 330-341

Henle, K., Alard, D., Clitherow, J., Cobb, P., Firbank, L., Kull, T., McCracken, D., Moritz, R.F.A., Niemelä, J., Rebane, M., Wascher, D., Watt, A., & Young, J. (2008). Identifying and managing the conflicts between agriculture and biodiversity conservation in Europe–A review. *Agriculture, Ecosystems & Environment, 124*, 60-71

Herzog, F., Steiner, B., Bailey, D., Baudry, J., Billeter, R., Bukácek, R., De Blust, G., De Cock, R., Dirksen, J., Dormann, C.F., De Filippi, R., Frossard, E., Liira, J., Schmidt, T., Stöckli, R., Thenail, C., van Wingerden, W., & Bugter, R. (2006). Assessing the intensity of temperate European agriculture at the landscape scale. *European Journal of Agronomy, 24*, 165-181

Hickler, T., Vohland, K., Feehan, J., Miller, P.A., Smith, B., Costa, L., Giesecke, T., Fronzek, S., Carter, T.R., Cramer, W., Kühn, I., & Sykes, M.T. (2012). Projecting the future distribution of European potential natural vegetation zones with a generalized, tree species-based dynamic vegetation model. *Global Ecology and Biogeography, 21*, 50-63

Hilker, T., Natsagdorj, E., Waring, R.H., Lyapustin, A., & Wang, Y. (2014). Satellite observed widespread decline in Mongolian grasslands largely due to overgrazing. *Global Change Biology, 20*, 418-428

Höchtl, F., Lehringer, S., & Konold, W. (2005). “Wilderness”: what it means when it becomes a reality—a case study from the southwestern Alps. *Landscape and Urban Planning, 70*, 85-95

Hopkins, A. (2006). Grasslands: developments, opportunities, perspectives. *Grass and Forage Science, 61*, 200-200

Hostert, P., Kuemmerle, T., Prishchepov, A., Sieber, A., Lambin, E.F., & Radeloff, V.C. (2011). Rapid land use change after socio-economic disturbances: the collapse of the Soviet Union versus Chernobyl. *Environmental Research Letters, 6*

Huete, A., Didan, K., Leeuwen, W., Miura, T., & Glenn, E. (2011). MODIS Vegetation Indices. In B. Ramachandran, C.O. Justice, & M.J. Abrams (Eds.), *Land Remote Sensing and Global Environmental Change* (pp. 579-602): Springer New York

Huyghe, C., De Vliegher, A., Van Gils, B., & Peeters, A. (2014). *Grasslands and herbivore production in Europe and effects of common policies*.

Ioffe, G., Nefedova, T., & deBeurs, K. (2012). Land abandonment in Russia: A case study of two regions. *Eurasian geography and economics: formerly Post-Soviet geography and economics, 53*, 527-549

Jepsen, M.R., Kuemmerle, T., Müller, D., Erb, K., Verburg, P.H., Haberl, H., Vesterager, J.P., Andrič, M., Antrop, M., Austrheim, G., Björn, I., Bondeau, A., Bürgi, M., Bryson, J., Caspar, G., Cassar, L.F., Conrad, E., Chromý, P., Daugirdas, V., Van Eetvelde, V., Elena-

Rosselló, R., Gimmi, U., Izakovicova, Z., Jančák, V., Jansson, U., Kladnik, D., Kozak, J., Konkoly-Gyuró, E., Krausmann, F., Mander, Ü., McDonagh, J., Pärn, J., Niedertscheider, M., Nikodemus, O., Ostapowicz, K., Pérez-Sobaa, M., Pinto-Correia, T., Ribokas, G., Rounsevell, M., Schistou, D., Schmit, C., Terkenli, T.S., Tretvik, A.M., Trzepacz, P., Vadineanu, A., Walz, A., Zhllima, E., & Reenberg, A. (2015). Transitions in European land-management regimes between 1800 and 2010. *Land Use Policy, under review*

Jin, S., & Sader, S.A. (2005). MODIS time-series imagery for forest disturbance detection and quantification of patch size effects. *Remote Sensing of Environment, 99*, 462-470

Johnson, D.M. (2013). A 2010 map estimate of annually tilled cropland within the conterminous United States. *Agricultural Systems, 114*, 95-105

Johnston, M., Licker, R., Foley, J., Holloway, T., Mueller, N.D., Barford, C., & Kucharik, C. (2011). Closing the gap: global potential for increasing biofuel production through agricultural intensification. *Environmental Research Letters, 6*

Jönsson, A.M., Eklundh, L., Hellström, M., Bärring, L., & Jönsson, P. (2010). Annual changes in MODIS vegetation indices of Swedish coniferous forests in relation to snow dynamics and tree phenology. *Remote Sensing of Environment, 114*, 2719-2730

Jönsson, P., & Eklundh, L. (2004). TIMESAT—a program for analyzing time-series of satellite sensor data. *Computers & Geosciences, 30*, 833-845

Kastner, T., Erb, K.-H., & Haberl, H. (2014). Rapid growth in agricultural trade: effects on global area efficiency and the role of management. *Environmental Research Letters, 9*

Kastner, T., Erb, K.-H., & Nonhebel, S. (2011). International wood trade and forest change: A global analysis. *Global Environmental Change, 21*, 947-956

Kawamura, K., Akiyama, T., Yokota, H.-o., Tsutsumi, M., Yasuda, T., Watanabe, O., & Wang, S. (2005). Quantifying grazing intensities using geographic information systems and satellite remote sensing in the Xilingol steppe region, Inner Mongolia, China. *Agriculture, Ecosystems & Environment, 107*, 83-93

Keenleyside, C., Tucker, G., & McConville, A. (2010). Farmland Abandonment in the EU: an assessment of trends and prospects. *London: WWF and IEEP*, 97pp.

Keyzer, M.A., Merbis, M.D., Pavel, I.F.P.W., & van Wesenbeeck, C.F.A. (2005). Diet shifts towards meat and the effects on cereal use: can we feed the animals in 2030? *Ecological Economics, 55*, 187-202

Kleijn, D., Kohler, F., Báldi, A., Batáry, P., Concepción, E.D., Clough, Y., Díaz, M., Gabriel, D., Holzschuh, A., Knop, E., Kovács, A., Marshall, E.J.P., Tscharntke, T., & Verhulst, J. (2009). On the relationship between farmland biodiversity and land-use intensity in Europe. *Proceedings of the Royal Society B: Biological Sciences, 276*, 903-909

Kohonen, T. (2001). *Self-Organizing Maps*. (3rd ed.). Berlin, New York, Amsterdam: Springer

Koning, N.B.J., Van Ittersum, M.K., Becx, G.A., Van Boekel, M.A.J.S., Brandenburg, W.A., Van Den Broek, J.A., Goudriaan, J., Van Hofwegen, G., Jongeneel, R.A., Schiere, J.B., & Smies, M. (2008). Long-term global availability of food: continued abundance or new scarcity? *NJAS - Wageningen Journal of Life Sciences, 55*, 229-292

Krausmann, F., Erb, K.-H., Gingrich, S., Haberl, H., Bondeau, A., Gaube, V., Lauk, C., Plutzar, C., & Searchinger, T.D. (2013). Global human appropriation of net primary production doubled in the 20th century. *Proceedings of the National Academy of Sciences, 110*, 10324-10329

Kuemmerle, T., Erb, K., Meyfroidt, P., Müller, D., Verburg, P.H., Estel, S., Haberl, H., Hostert, P., Jepsen, M.R., Kastner, T., Levers, C., Lindner, M., Plutzar, C., Verkerk, P.J., van der Zanden, E.H., & Reenberg, A. (2013). Challenges and opportunities in mapping land use intensity globally. *Current Opinion in Environmental Sustainability, 5*, 484-493

Kuemmerle, T., Hostert, P., Radeloff, V., van der Linden, S., Perzanowski, K., & Kruhlov, I. (2008). Cross-border Comparison of Post-socialist Farmland Abandonment in the Carpathians. *Ecosystems, 11*, 614-628

Kuemmerle, T., Müller, D., Griffiths, P., & Rusu, M. (2009). Land use change in Southern Romania after the collapse of socialism. *Regional Environmental Change, 9*, 1-12

Kuemmerle, T., Olofsson, P., Chaskovskyy, O., Baumann, M., Ostapowicz, K., Woodcock, C.E., Houghton, R.A., Hostert, P., Keeton, W.S., & Radeloff, V.C. (2011). Post-Soviet farmland abandonment, forest recovery, and carbon sequestration in western Ukraine. *Global Change Biology, 17*, 1335-1349

Laliberté, E., Wells, J.A., DeClerck, F., Metcalfe, D.J., Catterall, C.P., Queiroz, C., Aubin, I., Bonser, S.P., Ding, Y., Fraterrigo, J.M., McNamara, S., Morgan, J.W., Merlos, D.S., Vesk, P.A., & Mayfield, M.M. (2010). Land-use intensification reduces functional redundancy and response diversity in plant communities. *Ecology Letters, 13*, 76-86

Lambin, E.F., Gibbs, H.K., Ferreira, L., Grau, R., Mayaux, P., Meyfroidt, P., Morton, D.C., Rudel, T.K., Gasparri, I., & Munger, J. (2013). Estimating the world's potentially available cropland using a bottom-up approach. *Global Environmental Change, 23*, 892-901

Lambin, E.F., & Meyfroidt, P. (2011). Global land use change, economic globalization, and the looming land scarcity. *Proceedings of the National Academy of Sciences, 108*, 3465-3472

Lambin, E.F., Turner, B.L., Geist, H.J., Agbola, S.B., Angelsen, A., Bruce, J.W., Coomes, O.T., Dirzo, R., Fischer, G., & Folke, C. (2001). The causes of land-use and land-cover change: moving beyond the myths. *Global Environmental Change, 11*, 261-269

Larsson, S., & Nilsson, C. (2005). A remote sensing methodology to assess the costs of preparing abandoned farmland for energy crop cultivation in northern Sweden. *Biomass and Bioenergy, 28*, 1-6

Laurance, W.F., Sayer, J., & Cassman, K.G. (2014). Agricultural expansion and its impacts on tropical nature. *Trends in Ecology & Evolution, 29*, 107-116

Lefebvre, M., Espinosa, M., Gomez, Y., & Paloma, S. (2012). The influence of the Common Agricultural Policy on agricultural landscapes. In J.S.a.P. Reports (Ed.). Seville, Spain,: Institute for Prospective. Technological Studies - Joint Research Centre of the European Commission

Lemaire, G., Wilkins, R., & Hodgson, J. (2005). Challenges for grassland science: managing research priorities. *Agriculture, Ecosystems & Environment, 108*, 99-108

Lerman, Z. (2004). *Agriculture in transition : land policies and evolving farm structures in post-Soviet countries*. Lanham [u.a.] : Lexington Books

Lerman, Z., & Shagaida, N. (2007). Land policies and agricultural land markets in Russia. *Land Use Policy, 24*, 14-23

Li, L., Friedl, M.A., Xin, Q., Gray, J., Pan, Y., & Frolking, S. (2014). Mapping Crop Cycles in China Using MODIS-EVI Time Series. *Remote Sensing, 6*, 2473-2493

Licker, R., Johnston, M., Foley, J.A., Barford, C., Kucharik, C.J., Monfreda, C., & Ramankutty, N. (2010). Mind the gap: how do climate and agricultural management explain the 'yield gap' of croplands around the world? *Global Ecology and Biogeography, 19*, 769-782

Linnell, J.D.C., Kaczensky, P., Wotschikowsky, U., Lescureux, N., & Boitani, L. (2015). Framing the relationship between people and nature in the context of European conservation. *Conservation Biology, 29*, 978-985

Lionello, P., Abrantes, F., Congedi, L., Dulac, F., Gacic, M., Gomis, D., Goodess, C., Hoff, H., Kutiel, H., Luterbacher, J., Planton, S., Reale, M., Schröder, K., Vittoria Struglia, M., Toreti, A., Tsimplis, M., Ulbrich, U., & Xoplaki, E. (2012). Introduction: Mediterranean Climate—Background Information. In P. Lionello (Ed.), *The Climate of the Mediterranean Region* (pp. xxxv-xc). Oxford: Elsevier

MacDonald, D., Crabtree, J.R., Wiesinger, G., Dax, T., Stamou, N., Fleury, P., Gutierrez Lazpita, J., & Gibon, A. (2000). Agricultural abandonment in mountain areas of Europe: Environmental consequences and policy response. *Journal of Environmental Management, 59*, 47-69

Mader, S. (2012). A Framework for the Phenological Analysis of Hypertemporal Remote Sensing Data Based on Polynomial Spline Models. In, *Geographie/Geowissenschaften*. https://www.uni-trier.de/index.php?id=13817: Trier University

Matson, P.A., Parton, W.J., Power, A.G., & Swift, M.J. (1997). Agricultural Intensification and Ecosystem Properties. *Science, 277*, 504-509

Maulik, U., & Bandyopadhyay, S. (2002). Performance evaluation of some clustering algorithms and validity indices. *Pattern Analysis and Machine Intelligence, IEEE Transactions on, 24*, 1650-1654

Meyfroidt, P., & Lambin, E.F. (2011). Global Forest Transition: Prospects for an End to Deforestation. *Annual Review of Environment and Resources, 36*, 343-371

Meyfroidt, P., Rudel, T.K., & Lambin, E.F. (2010). Forest transitions, trade, and the global displacement of land use. *Proceedings of the National Academy of Sciences*

Monfreda, C., Ramankutty, N., & Foley, J.A. (2008). Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global Biogeochemical Cycles, 22*, GB1022

Moran, P.A.P. (1950). Notes On Continuous Stochastic Phenomena. *Biometrika, 37*, 17-23

Moreira, F., & Russo, D. (2007). Modelling the impact of agricultural abandonment and wildfires on vertebrate diversity in Mediterranean Europe. *Landscape Ecology, 22*, 1461-1476

Mueller, N.D., Gerber, J.S., Johnston, M., Ray, D.K., Ramankutty, N., & Foley, J.A. (2012). Closing yield gaps through nutrient and water management. *Nature, 490*, 254-257

Müller, D., Leitão, P.J., & Sikor, T. (2013). Comparing the determinants of cropland abandonment in Albania and Romania using boosted regression trees. *Agricultural Systems, 117*, 66-77

Mustard, J., Defries, R., Fisher, T., & Moran, E. (2004). Land-Use and Land-Cover Change Pathways and Impacts. In G. Gutman, A. Janetos, C. Justice, E. Moran, J. Mustard, R. Rindfuss, D. Skole, B. Turner, II, & M. Cochrane (Eds.), *Land Change Science* (pp. 411-429): Springer Netherlands

Neumann, K., Elbersen, B., Verburg, P., Staritsky, I., Pérez-Soba, M., de Vries, W., & Rienks, W. (2009). Modelling the spatial distribution of livestock in Europe. *Landscape Ecology, 24*, 1207-1222

Neumann, K., Verburg, P.H., Stehfest, E., & Müller, C. (2010). The yield gap of global grain production: A spatial analysis. *Agricultural Systems, 103*, 316-326

Niedertscheider, M., Kuemmerle, T., Müller, D., & Erb, K. (2015). Exploring the effects of drastic institutional and socio-economic changes on land system dynamics in Germany between 1883 and 2007. *Global Environmental Change, 28*

Olofsson, P., Foody, G.M., Stehman, S.V., & Woodcock, C.E. (2013). Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. *Remote Sensing of Environment, 129*, 122-131

Overmars, K.P., Schulp, C.J.E., Alkemade, R., Verburg, P.H., Temme, A.J.A.M., Omtzigt, N., & Schaminée, J.H.J. (2014). Developing a methodology for a species-based and spatially explicit indicator for biodiversity on agricultural land in the EU. *Ecological Indicators, 37, Part A*, 186-198

Ozdogan, M., & Gutman, G. (2008). A new methodology to map irrigated areas using multi-temporal MODIS and ancillary data: An application example in the continental US. *Remote Sensing of Environment, 112*, 3520-3537

Ozdogan, M., & Woodcock, C.E. (2006). Resolution dependent errors in remote sensing of cultivated areas. *Remote Sensing of Environment, 103*, 203-217

Ozdogan, M., Woodcock, C.E., Salvucci, G.D., & Demir, H. (2006). Changes in Summer Irrigated Crop Area and Water Use in Southeastern Turkey from 1993 to 2002: Implications for Current and Future Water Resources. *Water Resources Management, 20*, 467-488

Parr, C.L., Lehmann, C.E.R., Bond, W.J., Hoffmann, W.A., & Andersen, A.N. (2014). Tropical grassy biomes: misunderstood, neglected, and under threat. *Trends in Ecology & Evolution, 29*, 205-213

Penov, I. (2004). The Use of Irrigation Water in Bulgaria's Plovdiv Region During Transition. *Environmental Management, 34*, 304-313

Pettorelli, N., Laurance, W.F., O'Brien, T.G., Wegmann, M., Nagendra, H., & Turner, W. (2014a). Satellite remote sensing for applied ecologists: opportunities and challenges. *Journal of Applied Ecology*, n/a-n/a

Pettorelli, N., Safi, K., & Turner, W. (2014b). Satellite remote sensing, biodiversity research and conservation of the future. *Philosophical Transactions of the Royal Society B: Biological Sciences, 369*, 20130190-20130190

Pittman, K., Hansen, M.C., Becker-Reshef, I., Potapov, P.V., & Justice, C.O. (2010). Estimating Global Cropland Extent with Multi-year MODIS Data. *Remote Sensing, 2*, 1844-1863

Pointereau, P., Coulon, F., Girard, P., Lambotte, M., Stuczynski, T., Sanchez Ortega, V., & Del Rio, A. (2008). Analysis of Farmland Abandonment and the Extent and Location of Agricultural Areas that are Actually Abandoned or are in Risk to be Abandoned. In E. Anguiano, C. Bamps, & J.-M. Terres (Eds.), *JRC Scientific and Technical Reports (EUR 23411 EN)*

Portmann, F.T., Siebert, S., & Döll, P. (2010). MIRCA2000—Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling. *Global Biogeochemical Cycles, 24*, GB1011

Poschlod, P., & Bonn, S. (1998). Changing dispersal processes in the central European landscape since the last ice age: An explanation for the actual decrease of plant species richness in different habitats? *Acta Botanica Neerlandica, 47*, 27-44

Potter, P., Ramankutty, N., Bennett, E.M., & Donner, S.D. (2010). Characterizing the Spatial Patterns of Global Fertilizer Application and Manure Production. *Earth Interactions, 14*, 1-22

Prishchepov, A.V., Radeloff, V.C., Baumann, M., Kuemmerle, T., & Müller, D. (2012a). Effects of institutional changes on land use: agricultural land abandonment during the transition from state-command to market-driven economies in post-Soviet Eastern Europe. *Environmental Research Letters, 7*

Prishchepov, A.V., Radeloff, V.C., Dubinin, M., & Alcantara, C. (2012b). The effect of Landsat ETM/ETM+ image acquisition dates on the detection of agricultural land abandonment in Eastern Europe. *Remote Sensing of Environment, 126*, 195-209

R Core Team (2014). R: A language and environment for statistical computing. In. Vienna, Austria: R Foundation for Statistical Computing

Rabe, A., Jakimow, B., Held, M., van der Linden, S., & Hostert, P. (2014). EnMAP-Box, Version 2.0, software available at www.enmap.org

Ramankutty, N., & Foley, J.A. (1998). Characterizing patterns of global land use: An analysis of global croplands data. *Global Biogeochemical Cycles, 12*, 667-685

Ramankutty, N., Foley, J.A., Norman, J., & McSweeney, K. (2002). The global distribution of cultivable lands: current patterns and sensitivity to possible climate change. *Global Ecology and Biogeography, 11*, 377-392

Ray, D.K., & Foley, J.A. (2013). Increasing global crop harvest frequency: recent trends and future directions. *Environmental Research Letters, 8*, 44041-44050

Renwick, A., Jansson, T., Verburg, P.H., Revoredo-Giha, C., Britz, W., Gocht, A., & McCracken, D. (2013). Policy reform and agricultural land abandonment in the EU. *Land Use Policy, 30*, 446-457

Rey Benayas, J. (2007). Abandonment of agricultural land: an overview of drivers and consequences. *CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources, 2*

Rindfuss, R.R., Walsh, S.J., Turner, B.L., Fox, J., & Mishra, V. (2004). Developing a science of land change: Challenges and methodological issues. *Proceedings of the National Academy of Sciences of the United States of America, 101*, 13976-13981

Ritchie, M. (2014). Validation of a remote sensing method of estimating grazing impacts in northern Kenya rangelands. In A.B.C. Group (Ed.). http://www.abcg.org/document_details?document_id=665

Robinson, T.P., Wint, G.R.W., Conchedda, G., T.P., V.B., Ercoli, V., & Palamara, E. (2014). Mapping the Global Distribution of Livestock. *PLoS ONE, 9*

Rogan, J., & Chen, D. (2004). Remote sensing technology for mapping and monitoring land-cover and land-use change. *Progress in Planning, 61*, 301-325

Roques, S., Garstang, J., Kindred, D., Wiltshire, J., Tompkins, S., & Sylvester-Bradley, R. (2011). Idle land for future crop production. *World Agriculture, 2*, 40-42

Rötzer, T., & Chmielewski, F.-M. (2001). Phenological maps of Europe. *Climate Research, 18*, 249-257

Rounsevell, M.D.A., Pedroli, B., Erb, K.-H., Gramberger, M., Busck, A.G., Haberl, H., Kristensen, S., Kuemmerle, T., Lavorel, S., Lindner, M., Lotze-Campen, H., Metzger, M.J., Murray-Rust, D., Popp, A., Pérez-Soba, M., Reenberg, A., Vadineanu, A., Verburg, P.H., & Wolfslehner, B. (2012). Challenges for land system science. *Land Use Policy, 29*, 899-910

Rozelle, S., & Swinnen, J.F.M. (2004). Success and Failure of Reform: Insights from the Transition of Agriculture. *Journal of Economic Literature, 42*, 404-456

Rudel, T.K., Schneider, L., Uriarte, M., Turner Ii, B.L., DeFries, R., Lawrence, D., Geoghegan, J., Hecht, S., Ickowitz, A., & Lambin, E.F. (2009). Agricultural intensification and changes in cultivated areas, 1970–2005. *Proceedings of the National Academy of Sciences, 106*, 20675-20680

Ruiz-Flan˜o, P., Garcia-Ruiz, J.M., & Ortigosa, L. (1992). Geomorphological evolution of abandoned fields. A case study in the Central Pyrenees. *CATENA, 19*, 301-308

Sakamoto, T., Van Phung, C., Kotera, A., Nguyen, K.D., & Yokozawa, M. (2009). Analysis of rapid expansion of inland aquaculture and triple rice-cropping areas in a coastal area of the Vietnamese Mekong Delta using MODIS time-series imagery. *Landscape and Urban Planning, 92*, 34-46

Sala, O.E., Stuart Chapin , F., III, Armesto, J.J., Berlow, E., Bloomfield, J., Dirzo, R., Huber-Sanwald, E., Huenneke, L.F., Jackson, R.B., Kinzig, A., Leemans, R., Lodge, D.M., Mooney, H.A., Oesterheld, M.n., Poff, N.L., Sykes, M.T., Walker, B.H., Walker, M., & Wall, D.H. (2000). Global Biodiversity Scenarios for the Year 2100. *Science, 287*, 1770-1774

Salmon, J.M., Friedl, M.A., Frolking, S., Wisser, D., & Douglas, E.M. (2015). Global rain-fed, irrigated, and paddy croplands: A new high resolution map derived from remote sensing, crop inventories and climate data. *International Journal of Applied Earth Observation and Geoinformation, 38*, 321-334

Sanderson, M.A., Goslee, S.C., Soder, K.J., Skinner, R.H., Tracy, B.F., & Deak, A. (2007). Plant species diversity, ecosystem function, and pasture Management—A perspective. *Canadian Journal of Plant Science, 87*, 479-487

Schierhorn, F., Faramarzi, M., Prishchepov, A.V., Koch, F.J., & Müller, D. (2014). Quantifying yield gaps in wheat production in Russia. *Environmental Research Letters, 9*

Schierhorn, F., Müller, D., Beringer, T., Prishchepov, A.V., Kuemmerle, T., & Balmann, A. (2013). Post-Soviet cropland abandonment and carbon sequestration in European Russia, Ukraine, and Belarus. *Global Biogeochemical Cycles, 27*, 1175-1185

Schuster, C., Schmidt, T., Conrad, C., Kleinschmit, B., & Förster, M. (2015). Grassland habitat mapping by intra-annual time series analysis – Comparison of RapidEye and TerraSAR-X satellite data. *International Journal of Applied Earth Observation and Geoinformation, 34*, 25-34

Sieber, A., Kuemmerle, T., Prishchepov, A.V., Wendland, K.J., Baumann, M., Radeloff, V.C., Baskin, L.M., & Hostert, P. (2013). Landsat-based mapping of post-Soviet land-use change to assess the effectiveness of the Oksky and Mordovsky protected areas in European Russia. *Remote Sensing of Environment, 133*, 38-51

Siebert, S., Burke, J., Faures, J.M., Frenken, K., Hoogeveen, J., Döll, P., & Portmann, F.T. (2010a). Groundwater use for irrigation – a global inventory. *Hydrol. Earth Syst. Sci., 14*, 1863-1880

Siebert, S., Hoogeveen, J., & Frenken, K. (2006). Irrigation in Africa, Europe and Latin America - Update of the Digital Global Map of Irrigation Areas to Version 4. *Frankfurt Hydrology Paper 05, Institute of Physical Geography, University of Frankfurt, Frankfurt am Main, Germany and Food and Agriculture Organization of the United Nations, Rome, Italy.*

Siebert, S., Portmann, F.T., & Döll, P. (2010b). Global patterns of cropland use intensity. *Remote Sensing, 2*, 1625-1643

Skupin, A., & Agarwal, P. (2008). Introduction: What is a Self-Organizing Map? In A. Skupin, & P. Agarwal (Eds.), *Self-Organising Maps* (pp. 1-20). The Atrium, Southern Gate, Chichester, West Sussex, PO198SQ, England: John Wiley & Sons Ltd.

Smit, H.J., Metzger, M.J., & Ewert, F. (2008). Spatial distribution of grassland productivity and land use in Europe. *Agricultural Systems, 98*, 208-219

Solano, R., Didan, K., Jacobson, A., & Huete, A. (2010). MODIS Vegetation Index User's Guide (MOD13 Series), Version 2.00, May 2010 (Collection 5), http://vip.arizona.edu/documents/MODIS/MODIS_VI_UsersGuide_01_2012.pdf (accessed 24.03.2015)

Spera, S.A., Cohn, A.S., VanWey, L.K., Mustard, J.F., Rudorff, B.F., Risso, J., & Adami, M. (2014). Recent cropping frequency, expansion, and abandonment in Mato Grosso, Brazil had selective land characteristics. *Environmental Research Letters, 9*

Stanchi, S., Freppaz, M., Agnelli, A., Reinsch, T., & Zanini, E. (2012). Properties, best management practices and conservation of terraced soils in Southern Europe (from Mediterranean areas to the Alps): A review. *Quaternary International, 265*, 90-100

Stellmes, M., Röder, A., Udelhoven, T., & Hill, J. (2013). Mapping syndromes of land change in Spain with remote sensing time series, demographic and climatic data. *Land Use Policy, 30*, 685-702

Stoate, C., Báldi, A., Beja, P., Boatman, N.D., Herzon, I., van Doorn, A., de Snoo, G.R., Rakosy, L., & Ramwell, C. (2009). Ecological impacts of early 21st century agricultural change in Europe – A review. *Journal of Environmental Management, 91*, 22-46

Strijker, D. (2005). Marginal lands in Europe—causes of decline. *Basic and Applied Ecology, 6*, 99-106

Sulla-Menashe, D., Friedl, M.A., Krankina, O.N., Baccini, A., Woodcock, C.E., Sibley, A., Sun, G., Kharuk, V., & Elsakov, V. (2011). Hierarchical mapping of Northern Eurasian land cover using MODIS data. *Remote Sensing of Environment, 115*, 392-403

Sutcliffe, L.M.E., Batáry, P., Kormann, U., Báldi, A., Dicks, L.V., Herzon, I., Kleijn, D., Tryjanowski, P., Apostolova, I., Arlettaz, R., Aunins, A., Aviron, S., Baležentienė, L., Fischer, C., Halada, L., Hartel, T., Helm, A., Hristov, I., Jelaska, S.D., Kaligarič, M., Kamp, J., Klimek, S., Koorberg, P., Kostiuková, J., Kovács-Hostyánszki, A., Kuemmerle, T., Leuschner, C., Lindborg, R., Loos, J., Maccherini, S., Marja, R., Máthé, O., Paulini, I., Proença, V., Rey-Benayas, J., Sans, F.X., Seifert, C., Stalenga, J., Timaeus, J., Török, P., van Swaay, C., Viik, E., & Tscharntke, T. (2015). Harnessing the biodiversity value of Central and Eastern European farmland. *Diversity and Distributions, 21*, 722-730

Sutherland, W.J. (2002). Restoring a sustainable countryside. *Trends in Ecology & Evolution, 17*, 148-150

Svetlitchnyi, A. (2009). Soil Erosion Induced Degradation of Agrolandscapes in Ukraine: Modeling, Computation and Prediction in Conditions of the Climate Changes. In P. Groisman, & S. Ivanov (Eds.), *Regional Aspects of Climate-Terrestrial-Hydrologic Interactions in Non-boreal Eastern Europe* (pp. 191-199): Springer Netherlands

Tate, K.R., & Ross, D.J. (1997). Elevated CO2 and moisture effects on soil carbon storage and cycling in temperate grasslands. *Global Change Biology, 3*, 225-235

Temme, A.J.A.M., & Verburg, P.H. (2011). Mapping and modelling of changes in agricultural intensity in Europe. *Agriculture, Ecosystems & Environment, 140*, 46-56

Terres, J.M., Nisini, L., & Anguiano, E. (2013). Assessing the risk of farmland abandonment in the EU - Final Report. EUR 25783 EN

Thenkabail, P., S.; Biradar, C.M., Noojipady, P., Dheeravath, V., Li, Y.V., M., Gumma, M., Gangalakunta, O.R.P., Turral, H., Cai, X., Vithanage, J., Schull, M.A., & Dutta, R. (2009). Global irrigated area map (GIAM), derived from remote sensing, for the end of the last millennium. *International Journal of Remote Sensing, 30*, 55

Thornton, P.K. (2010). Livestock production: recent trends, future prospects. *Philosophical Transactions of the Royal Society of London B: Biological Sciences, 365*, 2853-2867

Thornton, P.K., & Herrero, M. (2010). Potential for reduced methane and carbon dioxide emissions from livestock and pasture management in the tropics. *Proceedings of the National Academy of Sciences, 107*, 19667-19672

Tilman, D., Balzer, C., Hill, J., & Befort, B.L. (2011). Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences, 108*, 20260-20264

Tilman, D., Cassman, K.G., Matson, P.A., Naylor, R., & Polasky, S. (2002). Agricultural sustainability and intensive production practices. *Nature, 418*, 671-677

Toivonen, M., Herzon, I., & Helenius, J. (2013). Environmental fallows as a new policy tool to safeguard farmland biodiversity in Finland. *Biological Conservation, 159*, 355-366

Tscharntke, T., Batáry, P., & Dormann, C.F. (2011). Set-aside management: How do succession, sowing patterns and landscape context affect biodiversity? *Agriculture, Ecosystems & Environment, 143*, 37-44

Tscharntke, T., Clough, Y., Wanger, T.C., Jackson, L., Motzke, I., Perfecto, I., Vandermeer, J., & Whitbread, A. (2012). Global food security, biodiversity conservation and the future of agricultural intensification. *Biological Conservation, 151*, 53-59

Unser, M., Aldroubi, A., & Eden, M. (1993). B-spline signal processing: part I – theory. *IEEE Transactions on Signal Processing, 41*, 821-832

van der Zanden, E.H., Verburg, P.H., & Mücher, C.A. (2013). Modelling the spatial distribution of linear landscape elements in Europe. *Ecological Indicators, 27*, 125-136

Verburg, P., & Overmars, K. (2009). Combining top-down and bottom-up dynamics in land use modeling: exploring the future of abandoned farmlands in Europe with the Dyna-CLUE model. *Landscape Ecology, 24*, 1167-1181

Verburg, P., van Berkel, D., van Doorn, A., van Eupen, M., & van den Heiligenberg, H.R.M. (2010). Trajectories of land use change in Europe: a model-based exploration of rural futures. *Landscape Ecology, 25*, 217-232

Verburg, P.H., Neumann, K., & Nol, L. (2011). Challenges in using land use and land cover data for global change studies. *Global Change Biology, 17*, 974-989

Vitousek, P.M., Mooney, H.A., Lubchenco, J., & Melillo, J.M. (1997). Human Domination of Earth's Ecosystems. *Science, 277*, 494-499

Vos, W., & Meekes, H. (1999). Trends in European cultural landscape development: perspectives for a sustainable future. *Landscape and Urban Planning, 46*, 3-14

Walesiak, M., & Dudek, A. (2014). clusterSim: Searching for optimal clustering procedure for a data set. In

Wan, Z. (2006). Collection-5 MODIS Land Surface Temperature Products Users' Guide. http://www.icess.ucsb.edu/modis/LstUsrGuide/MODIS_LST_products_Users_guide_C5.pdf (accessed 24.03.2015)

Wardlow, B.D., & Egbert, S.L. (2008). Large-area crop mapping using time-series MODIS 250 m NDVI data: An assessment for the U.S. Central Great Plains. *Remote Sensing of Environment, 112*, 1096-1116

Wehrens, R., & Buydens, L.M.C. (2007). Self- and super-organizing maps in R: The kohonen package. *Journal of Statistical Software, 21*, 1-19

Weigelt, A., Weisser, W.W., Buchmann, N., & Scherer-Lorenzen, M. (2009). Biodiversity for multifunctional grasslands: equal productivity in high-diversity low-input and low-diversity high-input systems. *Biogeosciences, 6*, 1695-1706

West, P.C., Gerber, J.S., Engstrom, P.M., Mueller, N.D., Brauman, K.A., Carlson, K.M., Cassidy, E.S., Johnston, M., MacDonald, G.K., Ray, D.K., & Siebert, S. (2014). Leverage points for improving global food security and the environment. *Science, 345*, 325-328

Wilson, J.B., Peet, R.K., Dengler, J., & Pärtel, M. (2012). Plant species richness: the world records. *Journal of Vegetation Science, 23*, 796-802

Woodwell, G.M., Hobbie, J.E., Houghton, R.A., Melillo, J.M., Moore, B., Peterson, B.J., & Shaver, G.R. (1983). Global Deforestation: Contribution to Atmospheric Carbon Dioxide. *Science, 222*, 1081-1086

Zaks, D.P.M., & Kucharik, C.J. (2011). Data and monitoring needs for a more ecological agriculture. *Environmental Research Letters, 6*

Zhang, X., Friedl, M.A., Schaaf, C.B., & Strahler, A.H. (2004). Climate controls on vegetation phenological patterns in northern mid- and high latitudes inferred from MODIS data. *Global Change Biology, 10*, 1133-1145

Zhao, M., Heinsch, F.A., Nemani, R.R., & Running, S.W. (2005). Improvements of the MODIS terrestrial gross and net primary production global data set. *Remote Sensing of Environment, 95*, 164-176

Zhou, L., Kaufmann, R.K., Tian, Y., Myneni, R.B., & Tucker, C.J. (2003). Relation between interannual variations in satellite measures of northern forest greenness and climate between 1982 and 1999. *Journal of Geophysical Research: Atmospheres, 108*, 4004

Publikationen

PEER-REVIEWED JOURNAL ARTICLES

Kuemmerle, T., Erb, K., Meyfroidt, P., Müller, D., Verburg, P.H., Estel, S., Haberl, H., Hostert, P., Jepsen, M.R., Kastner, T., Levers, C., Lindner, M., Plutzar, C., Verkerk, P.J., van der Zanden, E.H., & Reenberg, A. (2013). Challenges and opportunities in mapping land use intensity globally. *Current Opinion in Environmental Sustainability*, 5, 484-493.

Luyssaert S., Jammet M., Stoy P.C., Estel S., Pongratz J., Ceschia E., Churkina G., Don A., Erb K.H., Ferlicoq M., Gielen B., Grünwald T., Houghton R.A., Klumpp K., Knohl A., Kolb T., Kuemmerle T., Laurila T., Lohila A., Loustau D., McGrath, M.J., Meyfroidt P., Moors E.J., Naudts, K., Novick K., Otto J., Pilegaard K., Pio C.A., Rambal S., Rebmann C., Ryder J., Suyker A.E., Varlagin A., Wattenbach M. & Dolman A.J. 2014. Beyond land cover change - effects of contemporary land management on surface climate. *Nature Climate Change*.

Estel, S., Kuemmerle, T., Alcántara, C., Levers, C., Prishchepov, A., & Hostert, P. (2015). Mapping farmland abandonment and recultivation across Europe using MODIS NDVI time series. *Remote Sensing of Environment*, 163, 312-325.

UNDER REVIEW

Estel S., Kuemmerle T., Levers C., Baumann M., A. & Hostert, P. 2015. Mapping cropland use intensity across Europe using MODIS NDVI time series. *Environmental Research letters*.

Kuemmerle, T., Levers, C., Erb, K., Estel, S., Jepsen, M.R., Kroisleitner, C., Müller, D., Plutzar, C., Stürck, J., Verkerk, P. J., Verburg, P. H. & Reenberg, A. 2015. Hotspots of land use change in Europe. *Environmental Research Letters*.

IN PREPARATION

Estel, S., Mader, S., Levers, C., Verburg, P., Baumann, M., and Kuemmerle, T. (2015). Mapping grassland management intensity in Europe combining satellite data and agricultural statistics, *in preparation for Environmental Research Letters.*

CONFERENCE CONTRIBUTIONS

Estel S., Hostert P., Kuemmerle T., Prishchepov A., Alcantara C., 2014. Mapping agricultural abandonment across Europe using MODIS time series, GLP Second Open Science Meeting, March (19-21), 2014, Berlin/Germany (Oral presentation).

Estel S., Kuemmerle T., Levers C. 2012. Mapping hotspots of forest disturbance across Europe, IAMO FORUM, 2012, Halle/Germany (Oral presentation).

Levers, C. , Kuemmerle, T., Erb, K-H., Estel, S., Haberl, H., Jepsen, M.R., Kroisleitner, C., Lindner, M., Müller, D., Plutzar, C., Stürck, J., Verburg, P.H., Verker, P.J., van der Zanden, E.H. & Reenberg, A. (2014). Hotspots and Archetypes of Land System Change in Europe.

Global Land Project - Open Science Meeting, Berlin, Germany. March 2014. (Oral presentation).

Eidesstattliche Erklärung

Hiermit erkläre ich, die vorliegende Dissertation selbstständig und ohne Verwendung unerlaubter Hilfe angefertigt zu haben. Die aus fremden Quellen direkt oder indirekt übernommenen Inhalte sind als solche kenntlich gemacht. Die Dissertation wird erstmalig und nur an der Humboldt-Universität zu Berlin eingereicht. Weiterhin erkläre ich, nicht bereits einen Doktortitel im Fach Geographie zu besitzen. Die dem Verfahren zu Grunde liegende Promotionsordnung ist mir bekannt.

Stephan Estel

Berlin, den 03.08.2016